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An Evaluation of Trend Detection Techniques for Use in Water Quality Monitoring Programs

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AN EVALUATION OF TREND DETECTION TECHNIQUES FOR USE IN WATER QUALITY MONITORING PROGRAMS

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Notice

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ABSTRACT

Information goals for a long-term water quality monitoring program to measure the impacts due to acid precipitation were developed using the Acid Precipitation Act of 1980 (PL 96-294, Title VII) as a basis. These broad information goals were refined to obtain statistical hypotheses for which statistical tests could be employed as part of a data analysis plan.

Seven statistical tests were identified as capable of providing the desired information regarding trends in individual systems. The tests were evaluated under various conditions (i.e., distribution shape, seasonality and serial correlation) in order to determine how well they might perform as part of a data analysis plan. A Monte Carlo simulation approach was used to evaluate the tests.

For annual sampling, the Kendall-tau (also known as the Mann-Kendall) test is recommended. For seasonal sampling, the Seasonal Kendall or analysis of covariance (ANOCOV) on ranks test is recommended.

SECTION 1
INTRODUCTION

A major purpose of the Acid Precipitation Act of 1980 (PL 96-294, Title VII) is to evaluate the environmental effects of acid precipitation. To accomplish this task, it is necessary to detect and understand the nature of trends in water quality associated with acid precipitation. The purpose of this final report is to examine the statistical characteristics of the water quality variables most pertinent to acidification, for example, acid neutralizing capacity (ANC), pH, and SO_4, and to use these characteristics, along with estimates of our anticipated ability to detect temporal trends of varying magnitudes, to develop a data analysis plan. The report focuses on the detection of trends over time and does not deal directly with causes or effects.

The long-term trend monitoring of sensitive surface waters, in addition to examining the water quality variables ANC, pH, and SO_4, focuses strictly on water populations associated with lakes and streams sensitive to acidification. These populations of concern have been defined by other components of the TIME project. The statistical characteristics of existing data from similar populations serve as the basis for selecting trend analysis approaches.

1.1 GOALS OF MONITORING

Section 702b of the Acid Precipitation Act of 1980 (PL 96-294) declares that one of its purposes is to "...evaluate the environmental effects of acid precipitation..." This broad, legal objective has been translated into more specific and detailed information requirements as part of the implementation of PL 96-294. The TIME goals, as published in "The Concept of Time" and repeated in Appendix A, make up part of this translation.

The TIME goal most relevant to the detection of long-term trends can be stated as follows: "Estimate the regional trends of surface water quality--acidification or recovery." This form of the goal statement avoids the concept of estimating the proportion of lakes exhibiting trends and refers strictly to the collective trend in a region. This information goal must be further refined into a statistically meaningful statement around which a statistically sound monitoring system can be designed. This refinement means stating the goal as a hypothesis that can be tested, using the data as it is collected.

The null hypothesis, as noted in the documents used to develop "The Concept of Time" report (TIME goals distributed at the Corvallis Workshop on April 28, 1987), is: "There are no long-term regional trends in acidification or recovery of surface waters." The alternate hypothesis is that a trend exists.

More specific monitoring objectives may be stated as follows:

a. To detect monotonic trends (generally increasing or generally decreasing over time) in data series, both seasonal and annual, for selected water quality variables in individual lakes at the 90% confidence level.
b. To detect monotonic trends in time series consisting of weighted averages of water quality observations over specified groups of lakes at the 90% confidence level.

This further refinement of the monitoring goals specifies the type of trends (monotonic) and confidence level (90%) that the data analysis plan must account for in the statistical procedures it employs. The water quality variables utilized in the data analysis plan, as noted earlier, are ANC, pH, and SO_4. It is assumed that the refinement of the legal goal to the TIME goal and then to the statistical hypothesis is correct and that it has been approved by those responsible for enacting and implementing PL 96-294, Title VII. The data analysis plan is based on this refinement. This design effort does not directly encompass the other goals listed in "The Concept of Time" report. Other individuals working on TIME are addressing these goals.

1.2 SCOPE OF REPORT

This report provides only the information described in the discussion in Section 1.1 on monitoring goals. The recommended data analysis plan is not designed to provide information other than that on water quality trends in individual and groups of lakes and streams impacted by acidic deposition. Physical, practical, hydrological, and statistical concerns developed elsewhere in the TIME studies dictate that sampling must be performed on an annual basis for a relatively large number of sites (lakes and streams) and on a seasonal basis--two to four samples per year--for a smaller number of sites (TIME Conceptual Plan, 1987). In this report, therefore, sampling frequencies are assumed to be limited to a range of quarterly to annually.

A univariate time series approach is used throughout. The single variable can be the concentration of a water quality constituent, the ratio of concentrations of two constituents, or a weighted average of concentrations over a group of lakes or streams. There is no explicit attempt to detect trends on a population-wide basis. Changes in populations are covered elsewhere within the TIME project.

This study concentrates on selecting trend analysis methods that are well matched to the statistical characteristics of TIME data series. The primary characteristics of concern are distribution shape (normality versus non-normality), seasonal variation, and serial correlation. At this stage there has been no attempt to incorporate the effects of hydrologic variables such as rainfall or acidic deposition into the recommended trend analysis procedures. The single exception to this is that flow correction is recommended as part of trend analysis in streams. Neither has there been an effort to explicitly account for inter-station correlation. The effect of correlation between stations is, however, briefly discusssed in section 4.2, Multiple Lakes.

1.3 OVERVIEW OF STUDY

The Acid Precipitation Act of 1980 has been reviewed and its goals, as stated earlier, have been identified. Ultimate users of the information to be derived from the monitoring program have agreed with these goals. Their approval is critical, as alternative formulations of the problem could lead to different data analysis plans. The National Research Council (1977, p. 32) notes the need to clearly formulate monitoring purposes and criteria that are mutually understood by the information users and the monitoring system designers and operators.

With the monitoring goals defined, the next step was to select data analysis procedures that would provide the required information in a statistically sound manner. In order to select statistical tests for the data analysis plan that would be well matched to both the goals and the anticipated data attributes, background data from several sources were studied, including the Long-term Monitoring (LTM) data set described in Newell et al. (1987), data from Environment Canada for Clearwater Lake, Ontario, and data from the U.S. Bureau of Reclamation for Twin Lakes, Colorado. From these data, we were able to infer the level of seasonal behavior, serial correlation, and non-normality that could be anticipated from TIME data.

The conclusions of this study were that TIME data can be expected to be seasonal in both mean and standard deviation, to be normally distributed in some cases and non-normally in others, and to occasionally exhibit low level serial correlation for quarterly observations. No conclusions regarding serial correlation of annual values were drawn.

In view of these data characteristics, we selected and evaluated several candidate tests for detecting trend. These tests included both parametric and nonparametric approaches. Several options for dealing with seasonality were included, and one test included a correction for serial correlation. The candidate trend tests were:

a. Analysis of covariance (ANOCOV)
b. Modified t-test
c. Kendall-tau following removal of seasonal means
d. Seasonal Kendall (SK)
e. Seasonal Kendall with serial correlation correction
f. ANOCOV on ranks
g. Modified "t" on ranks

We evaluated the candidate tests by comparing their performance under a Monte Carlo simulation study designed to reproduce the data characteristics anticipated from TIME data. The performance indices were actual significance level and power of trend detection. Based on Monte Carlo results, we recommend a single trend test for annual data and two tests for seasonal data.

SECTION 2
RECOMMENDATIONS

For annual sampling, the recommended test is the Kendall-tau, sometimes called the Mann-Kendall test for trend. The Mann-Kendall test is nonparametric and is a member of the class of tests called rank correlation methods, meaning that the test checks for a correlation between the ranks of data and time. The test is well known and is frequently recommended for use in water quality trend analysis (Gilbert, 1987). The test does not account for seasonal variation. Since, however, it is recommended for use with annual data only, no prior removal of seasonal means is necessary.

For seasonal (generally quarterly) sampling, two alternative tests are recommended: analysis of covariance (ANOCOV) on ranks or the seasonal Kendall test. Both tests are nonparametric and both tests performed very well under most of the conditions studied in the Monte Carlo analysis, i.e., seasonal variation and both normal and lognormal noise. Neither test performed well when observations were serially correlated. The only test that accounted for serial correlation, the "corrected" version of seasonal Kendall, exhibited low power compared to the other tests. It seemed to us that the reduction in power was too high a price to pay for insensitivity to serial correlation. Therefore, we do not recommend the corrected test, except for very long data records. This logic is discussed further in sections 3.1, 3.4, and 3.5, which provide more information on statistical methods and Monte Carlo evaluations.

SECTION 3
JUSTIFICATION OF RECOMMENDATIONS

3.1 MONITORING OBJECTIVE IN STATISTICAL TERMS

The goal of monitoring relevant to the trend detection portion of TIME is to determine whether general increases or decreases in observed values of water quality variables are statistically significant--as opposed to being the coincidental result of random or natural variability. The term "trend detection" might therefore be somewhat misleading. It is not generally possible for statistics to detect trends that are not apparent by inspection, especially for data records of short to moderate length--say 20 years or less. It is preferable to think of trend tests as a quantitative basis for deciding whether apparent trends are real.

Therefore in statistical terms, the objective of monitoring (and subsequent trend analysis) is to accept the null hypothesis of no trend with specified (high) probability when no real trend exists and to reject the null hypothesis with high probability when real trends do exist.

The definition of a "real" trend is somewhat subjective. For the purposes of this study, trend is defined as a general increase or decrease in observed values of some random variable over time. A real trend is one that results from physical or chemical changes, not from natural hydrologic variability. In the present case, a "real" change would be one caused by acidic deposition resulting from air pollution or by changes in acidic deposition rates resulting from increasing or decreasing air pollution. Changes in water quality resulting from natural variability in precipitation patterns would not be considered "real" for the purposes of this study.

In view of this definition of a real change or trend, it is necessary to acknowledge a significant limitation of the recommended statistical tests of trend. At this stage of the TIME project, there is no attempt to directly relate hydrologic factors such as precipitation or acidic deposition to water quality within the framework of routine data analysis, i.e., annual reports.

The recommended methods consider water quality variables individually and address the following question: "Given the observed variability in a set of observations, what is the probability that an observed pattern (of increases or decreases) resulted from a no-trend situation?" If this probability is higher than some prespecified level, called the significance level, the null hypothesis of no trend is accepted. If the probability is lower than the significance level, the null hypothesis is rejected.

This limited univariate approach should be sufficient for routine (annual) reporting. However, for selected subregions or watersheds, a more thorough level of trend analysis will be undertaken by TIME. This will include modeling of hydrologic-chemical relationships in an attempt to (1) explain trends that routine analyses have shown to be significant and (2) reduce background variability of water quality in order to improve the ability of trend detection tests to reject the null hypothesis when trends exist.

For clarity of future discussion, let us formally define three terms as follows:

a. "Trend" is a general increase or decrease in the value of observations of a particular variable over time. For the purpose of comparing statistical tests, trends are later assumed to be monotonic (one directional) and gradual (linear) for simulation purposes. For the overall TIME project, however, the concept of trends is more general and need not be limited to monotonic, linear, or even gradual trends. The procedures recommended for data analysis are appropriate under the more general concept. However, test performance in terms of ability to reject the null hypothesis depends on the nature of real trends being examined.

b. The "significance level" of a test, denoted by α, is the probability of rejecting the null hypothesis of no trend when it is true. The significance level is also referred to as the type I error. The "nominal significance level" of a test is the rejection probability when all of the assumptions underlying the test are satisfied and the test statistic follows its theoretical distribution. The nominal significance level is usually specified before a test is run. In practice, the assumptions associated with a given test are not satisfied exactly, and the true or "actual significance level" will be different from the nominal level. In water quality monitoring, the assumptions underlying tests may be seriously violated, and the actual significance level may be quite different from the nominal level. Since our knowledge of the variables being monitored is quite limited, however, the actual significance level is never known. We can only minimize the difference between nominal and actual levels through the use of tests based on assumptions that closely match the data characteristics and/or tests insensitive ("robust") to violations of underlying assumptions. In future discussion, the terms "significance level" and "nominal significance level" will be used interchangably, whereas the modifier "actual" will be explicitly included when it is needed. The term "confidence level" is defined as $1-\alpha$, where α is the nominal significance level. Recommended pre-test confidence levels for the data analysis plan are 90% and 95%, using two-sided tests.

c. The "power" of a test is defined as the probability of rejecting the null hypothesis when a real trend exists. Power may also be defined as $1-\beta$, where β is the Type II error or probability of accepting the null hypothesis when it is false (when a real trend exists).

   It would be ideal to be able maximize the power of a test and minimize the significance level. Unfortunately, there is a direct relationship between the two. For given population characteristics and given sample size, the power of a given test decreases with decreasing significance level. Thus, we are forced to make do with some sort of trade-off between the two (at least in the usual situation where both the resources and direction of a monitoring program limit the effective independent sample size available for testing).

   The power of a test also depends on the nature of the trend that really occurs. By "nature" of a trend, we mean the functional form (gradual, sudden, linear, polynomial, monotonic sinusoidal, etc.), the magnitude and duration, and the population changes, such as changing variance, that accompany or are considered part of the trend.

In ecosystem monitoring, the possibilities for the nature of trend are endless. There is, therefore, no way to specify the power of a given test in the real world. The best we can do is to consider a few types of trend (rigidly specifying functional form, magnitude, duration, and accompanying population changes for each) that roughly represent the real world possibilities. Using these hypothetical trend models, we can then identify the power of a given test under those trend models and use the results to objectively compare the performance of alternative statistical tests. We can also use models to represent the behavior of water quality under no-trend conditions and use these to compare the empirical (actual) significance levels of candidate statistical tests.

This approach, limited simulation of water quality random variables under varying trend magnitudes and assumed behavioral characteristics, was used to compare alternative trend tests. Recommendations were formulated based on a comparison of empirical significance levels and the power of candidate tests.

3.2 CHARACTERISTICS OF BACKGROUND OR HISTORICAL DATA

3.2.1 Description of Historical Data Sets

Historical data were used to establish a range of statistical properties that might be expected from TIME data and to provide case studies demonstrating the application of recommended statistical tests. Data were obtained from three sources: (1) LTM data (Newell et al., 1987; Newell, 1987), (2) Twin Lakes data (Sartoris, 1987), and (3) Clearwater Lake data (Nicholls, 1987).

The LTM data were collected in a variety of studies that used differing sampling and laboratory analysis techniques (Newell et al., 1987). Data from these different studies are therefore not comparable, but since we are interested only in general descriptions of statistical behavior at this point, the disparities are not of concern.

Table 3-1 lists the "best" LTM records in each National Lake Survey (NLS) region. Selection is based on length and completeness of record. Table 3-2 presents the 16 overall best LTM lakes and adds Twin Lakes and Clearwater Lakes for a total study data set of 19 lakes. The variables of primary interest are alkalinity or acid neutralizing capacity (ANC), sulfate concentration, and pH. For Twin Lakes, sulfate data were not available, and conductivity data were used instead.

3.2.2 Results of Characterization

3.2.2.1 Seasonality--

Several researchers have observed significant seasonal variation in lake water quality. There are also hydrologic reasons to assume that lake water quality often varies seasonally. The purpose of background data analysis was to establish the magnitude of seasonal changes that we might expect in both the mean and standard deviation of the water quality in TIME series of interest.

Before focusing on the 19 selected lakes in the study data set, researchers considered all of the LTM data from regions 1A, 1C, 3A, 1E, and 2 and streams. Regional mean values for ANC, $SO_4^=$, and pH were computed for each season along with regional standard deviations by season. Standard deviations were computed using deviations from the individual lake means. Seasons were defined as quarters, starting with winter, consisting of December, January, February.

The results are presented in Table 3-3 (a,b,c). Observe that variation in both means and standard deviations across the four seasons ranges from minimal to very large. All three variables show obvious seasonality in at least one region. Alkalinity shows more seasonality than sulfate. The ratio of maximum to minimum ranges from just over 1.0 up to 5.0 or more for both quarterly means and quarterly standard deviations in both ANC and $SO_4^=$. Negative ratios are possible for ANC. The idea that one season might be identified as having consistently lower variance does not seem to be supported.

TABLE 3-1. THE BEST DATA RECORDS FOR EACH NLS REGION

The number of records for each lake was found using the ANC data for a series of quarterly data and is given by: (Number of nonmissing points - number of missing points).

NLS-1E (Main)

Best 3:

1E1-132	(9-2)
1E1-133	(9-2)
1E1-135	(9-2)

NLS-1A (Adirondacks: NY)*

Best 11:

1A1-071	(15-0)
1A1-087	(15-0)
1A1-102	(15-0)
1A1-105	(15-0)
1A1-106	(15-0)
1A1-107	(15-0)
1A1-109	(15-0)
1A1-110	(15-0)
1A1-113	(15-0)
1A2-077	(15-0)
1A2-078	(15-0)

NLS-2 (Upper Midwest: MN, WI, MI)

Best 3:

2A2-065	(16-13)
2A3-005	(16-13)
2C1-029	(11-4)

NSL-3A (Southern Blue Ridge: NC, TN, GA)

Best 3:

3A1-010	(8-3)
3A2-066	(9-4)
3A3-104	(8-3)

NLS-1C (NH, VT)

Best 5:

1C1-091	(15-0)
1C1-093	(19-0)
1C1-097	(18-1)
1C1-064	(17-0)
1C3-075	(19-0)

LTM Streams (Southeastern U.S.)

Best 7:

01434010	(10-0)
0210108450	(10-0)
0210289715	(10-0)
0213299630	(10-0)
03039420	(12-0)
03079520	(10-0)
03079700	(10-0)

* Region NLS-1A also has a record of (40-3) with monthly data for each of the best data sets.

TABLE 3-2. THE 19 BEST OVERALL DATA RECORDS, ANC

NLS - 1C	
1C1-091	(15-0)
1C1-093	(19-0)
1C1-097	(18-1)
1C3-064	(17-0)
1C3-075	(19-9)
NLS 1A[1]	
1A1-071	(15-0)
1A1-087	(15-0)
1A1-102	(15-0)
1A1-105	(15-0)
1A1-106	(15-0)
1A1-107	(15-0)
1A1-109	(15-0)
1A1-110	(15-0)
1A1-113	(15-0)
1A2-077	(15-0)
1A2-078	(15-0)
TWIN[2]	
Site 2	(35-0)
Site 4	(35-0)
CLEARWATER[2]	
	(26-0)

[1] Region NLS-1A also has a record of (40-3) with monthly data for each of the best data sets.

[2] Twin and Clearwater Lakes were sampled more freqently than quarterly. Quarterly values were obtained by choosing the observation closest to the middle of the quarter.

TABLE 3-3. REGIONAL MEANS AND STANDARD DEVIATIONS

(a) Regional Means and Standard Deviations for Alkalinity ($\mu eq\ L^{-1}$)

Region	Season[1]	Mean	Stand. Dev.	Total Obs.[2]
NLS-1A	All	32.9	29.8	242
	1	23.0	11.4	57
	2	13.7	16.9	48
	3	48.7	27.8	75
	4	38.9	28.5	62
NLS-1C	All	49.3	17.8	448
	1	59.7	19.3	113
	2	27.4	7.2	86
	3	41.0	9.3	123
	4	52.6	11.2	117
NLS-3A	All	92.7	21.4	73
	1			0
	2	81.4	14.9	24
	3	87.9	21.4	14
	4	106.3	10.2	26
NLS-1E	All	15.3	7.0	44
	1			0
	2	13.8	3.5	15
	3	13.8	6.0	15
	4	22.0	5.0	10
NLS-2	All	51.5	20.3	292
	1			0
	2	47.9	25.5	116
	3	54.6	9.7	84
	4	52.4	11.9	89
Streams	All	56.0	44.0	162
	1	71.9	52.4	23
	2	33.1	13.0	21
	3	57.4	23.7	21
	4	71.0	39.2	61

1 The seasons are defined as follows: (1) December, January, and February, (2) March, April, and May, (3) June, July, and August, (4) September, October, and November.

2 The number of observations for each of the seasons may not add up to the total number of observations because of the short data records. Records with only one observation for a season were not used for computing the seasonal means and standard deviations.

TABLE 3-3. REGIONAL MEANS AND STANDARD DEVIATIONS (Continued)

(b) Regional Means and Standard Deviations for Sulfate

Region	Season[1]	Mean	Stand. Dev.	Total Obs.[2]
NLS-1A	All	121.6	12.4	257
	1	131.7	7.1	60
	2	119.2	5.2	51
	3	115.1	8.8	80
	4	121.8	10.6	66
NLS-1C	All	112.4	14.5	449
	1	123.6	10.6	114
	2	104.3	12.0	87
	3	108.4	10.7	121
	4	111.4	11.9	117
NLS-3A	All	38.8	7.0	82
	1			0
	2	39.9	4.4	26
	3	40.5	5.1	16
	4	38.7	6.4	30
NLS-1E	All	70.2	3.4	44
	1			0
	2	69.7	3.6	14
	3	69.0	3.2	15
	4	70.6	1.8	10
NLS-2	All	84.5	10.7	332
	1			0
	2	85.5	8.9	138
	3	83.8	11.6	88
	4	86.5	9.0	101
Streams	All	95.5	28.4	153
	1	159.9	9.3	17
	2	155.4	9.8	17
	3	158.1	6.0	17
	4	89.8	34.3	55

[1] The seasons are defined as follows: (1) December, January, and February, (2) March, April, and May, (3) June, July, and August, (4) September, October, and November.

[2] The number of observations for each of the seasons may not add up to the total number of observations because of the short data records. Records with only one observation for a season were not used for computing the seasonal means and standard deviations.

TABLE 3-3. REGIONAL MEANS AND STANDARD DEVIATIONS (Continued)

(c) Regional Means and Standard Deviations for pH

Region	Season[1]	Mean	Stand. Dev.	Total Obs.[2]
NLS-1A	All	5.77	0.395	257
	1	5.52	0.200	60
	2	5.51	0.286	51
	3	6.03	0.315	80
	4	5.88	0.303	66
NLS-1C	All	5.92	0.306	418
	1	5.78	0.191	85
	2	5.70	0.260	90
	3	6.02	0.212	119
	4	6.05	0.278	114
NLS-3A	All	6.51	0.421	80
	1			0
	2	6.40	0.369	25
	3	6.78	0.243	14
	4	6.42	0.340	30
NLS-1E	All	5.82	0.140	45
	1			0
	2	5.75	0.127	15
	3	5.88	0.113	15
	4	5.89	0.069	10
NLS-2	All	6.08	0.230	344
	1			0
	2	6.07	0.197	141
	3	6.16	0.180	95
	4	5.99	0.152	106
Streams	All	5.38	0.334	168
	1	5.75	0.184	25
	2	5.69	0.277	21
	3	6.09	0.159	21
	4	5.45	0.347	52

[1] The seasons are defined as follows: (1) December, January, and February, (2) March, April, and May, (3) June, July, and August, (4) September, October, and November.

[2] The number of observations for each of the seasons may not add up to the total number of observations because of the short data records. Records with only one observation for a season were not used for computing the seasonal means and standard deviations.

Figures 3-1 through 3-4 present ratios of maximum to minimum seasonal means and standard deviations for selected lakes in NLS subregions 1A and 1C. Tables 3-4, 3-5, and 3-6 present composite results for the same two regions and for Twin Lakes. These results are exemplary of the entire background data set, showing ANC as the most seasonal variable followed by sulfate. Maximum to minimum ratios range generally from about 1.0 to 2.0 for quarterly means and from 1.0 to 5.0 for standard deviations. Thus it appears that seasonal variation ranges from none to the case where the maximum quarterly mean and/or standard deviation is two to five times the minimum.

Due to small record length, no attempt was made to show that seasonality is statistically significant. However, a reasonable range of seasonality has been established for use in modeling.

There does not appear to be a consistent pattern or ordering of low or high values for any variable in either the mean or standard deviation.

3.2.2.2 Normality--

Data records from the "best" lakes were checked for normality using tests for both skewness and kurtosis. The skewness test determines whether the distribution is symmetrical about the mean. Data sets that have sample skewness coefficients differing significantly from zero (either positive or negative) are judged to be non-normal.

The sample kurtosis determines whether the distribution is too flat or too peaked compared to the normal distribution. Sample kurtosis values that differ significantly from 3.0 are judged to come from non-normal populations. From these results, the hypothesis of normality can be rejected on only about 20% of the two-tailed tests when they are applied at significance levels of 10% and 2% (5% and 1% for each tail).

Results are presented in Tables 3-7, 3-8, and 3-9 for skewness tests, and in Tables 3-10, 3-11, and 3-12 for kurtosis tests on raw data, log transformed data, and data with quarterly means removed. In general, the log transformation and removal of quarterly means did not increase or decrease the number of data records that appeared to be normal.

Although most of the records studied appeared to come from a normal distribution, a blanket assumption of normality for TIME monitoring would be unwise. Several variables do not appear to be normal, and many other studies of water quality random variables have shown that non-normality is frequently encountered. Thus, in general studies that, like TIME, cover diverse hydrologic conditions, we should be reluctant to place confidence in a normality assumption.

3.2.2.3 Serial Correlation--

Autocorrelation of a time series represents a carry-over of information from one observation to the next. Positive autocorrelation is the tendency of high values to follow high values or low values to follow low values. Negative autocorrelation is the tendency of high values to follow low values and vice versa. Autocorrelation in the absence of seasonality or trend is referred to as serial correlation. Both seasonality and serial correlation make trend detection more difficult.

The autocorrelation coefficient p(k) and its sample estimate r(k) range from +1 to -1. Correlograms or plots of the sample autocorrelation function, r(k), are useful as tools to check for seasonality and serial correlation. Figures 3-5 through 3-12 present correlograms for selected variables and lakes.

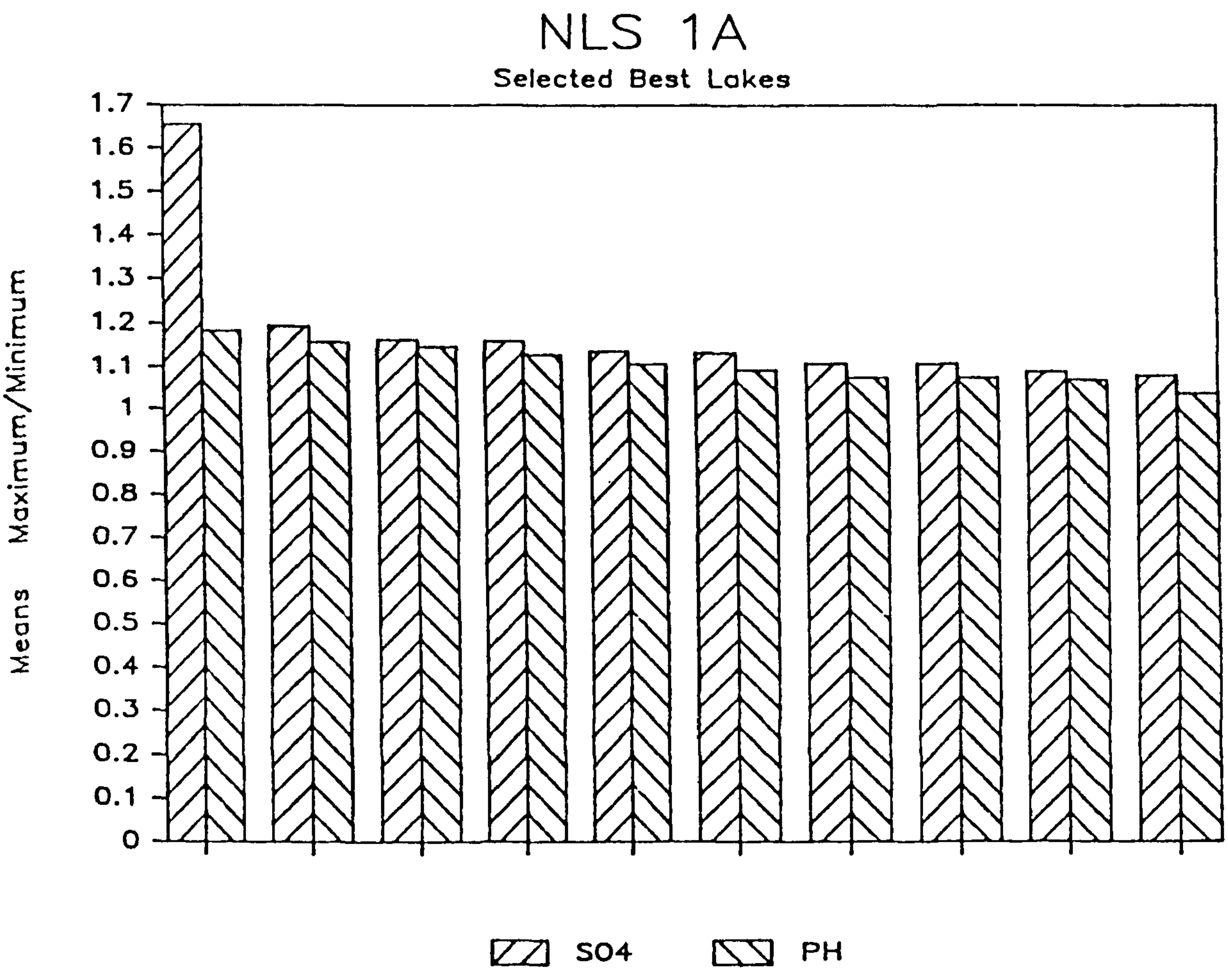


Figure 3-1. Seasonal variation in quarterly means for $SO_4^=$ and pH for selected lakes in NLS subregion 1A.

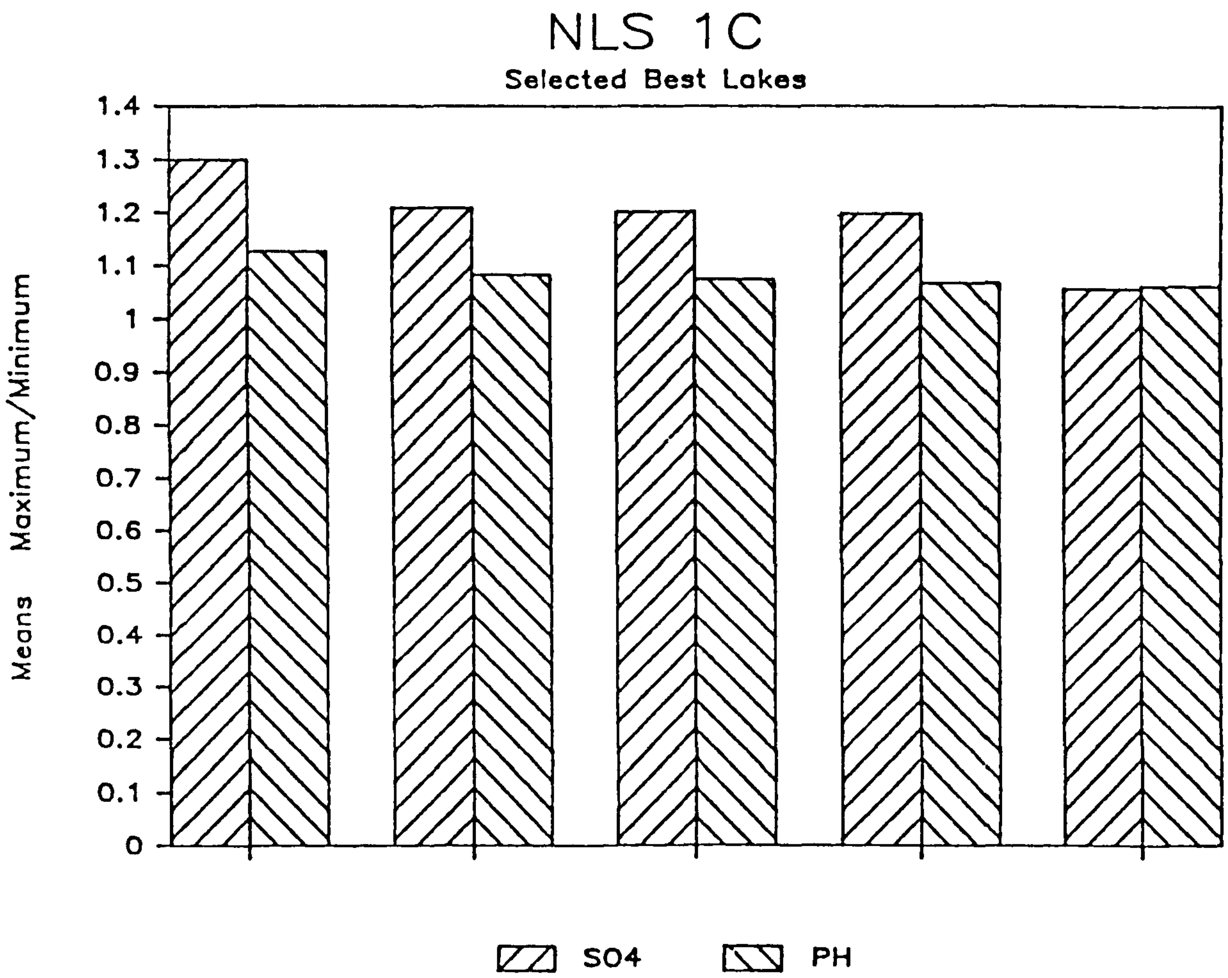


Figure 3-2. Seasonal variation in quarterly means for $SO_4^=$ and pH for selected lakes in NLS subregion 1C.

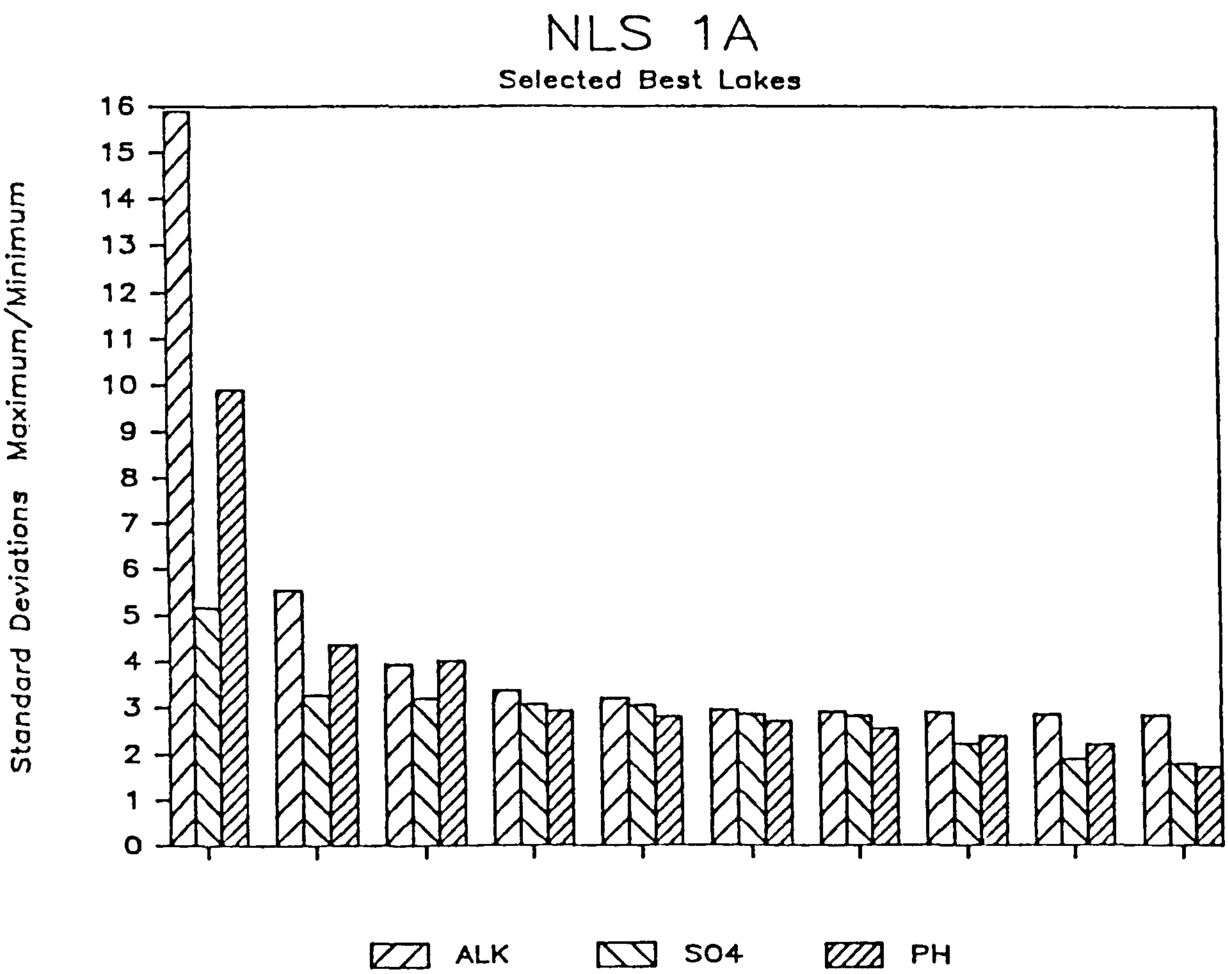


Figure 3-3. Seasonal variation in quarterly standard deviations for alkalinity, $SO_4^=$, and pH for selected lakes in NLS subregion 1A.

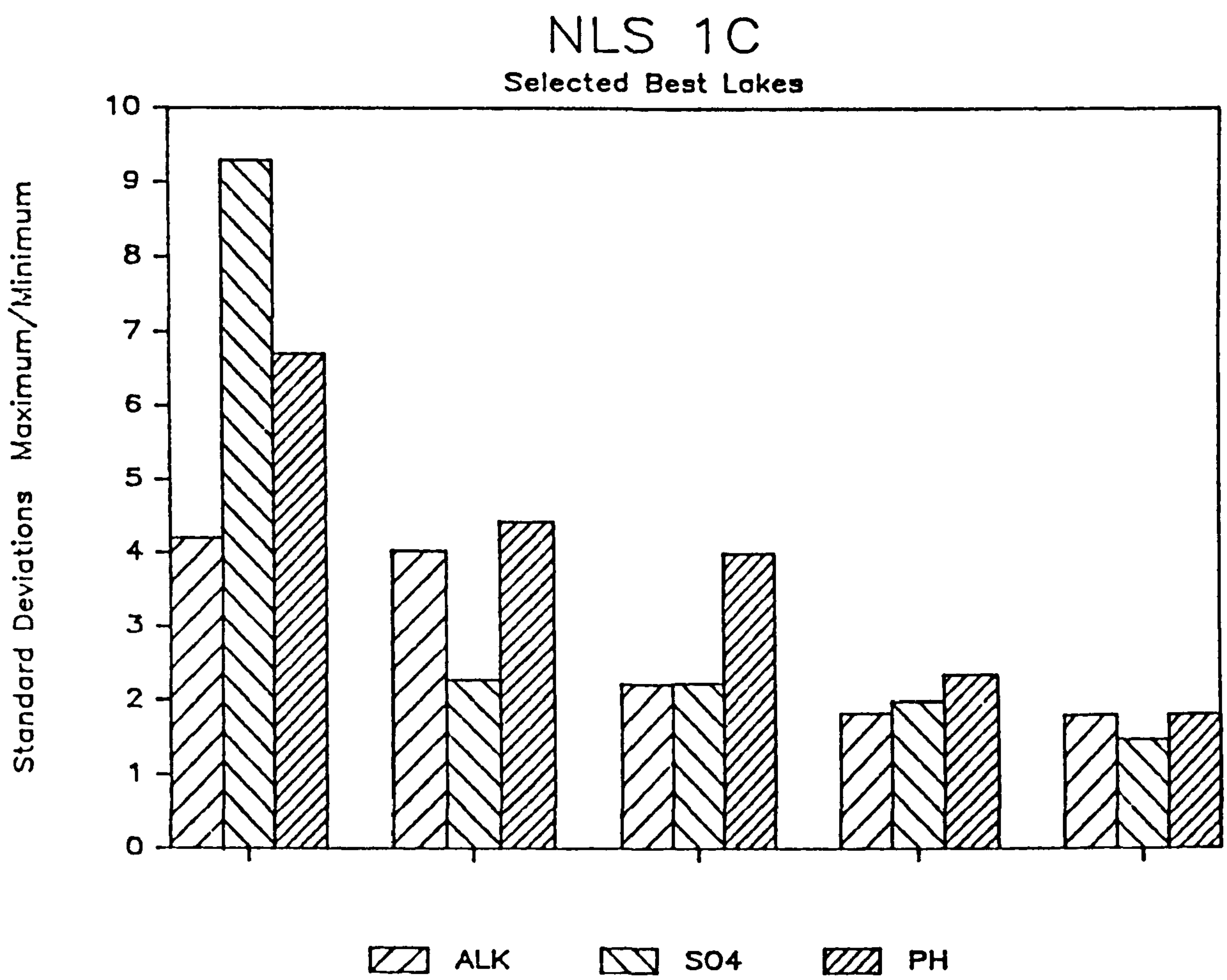


Figure 3-4. Seasonal variation in quarterly standard deviations for alkalinity, $SO_4^=$, and pH for selected lakes in NLS subregion 1C.

TABLE 3-4. REGIONAL MAXIMUM TO MINIMUM RATIOS OF QUARTERLY MEANS AND STANDARD DEVIATIONS FOR ALKALINITY

Region	Lake	Mean	Stand. Dev.
NLS-1A	Overall	3.70	2.49
	1A1-071	1.21	3.36
	1A1-087	4.91	2.82
	1A1-102	1.74	3.94
	1A1-105	2.74	5.55
	1A1-106	-1.02	2.84
	1A1-107	0.75	2.94
	1A1-109	1.89	3.19
	1A1-110	5.33	2.90
	1A2-077	1.37	15.89
	1A2-078	-7.96	2.88
NLS-1C	Overall	2.18	2.69
	1C1-091	1.51	2.22
	1C1-093	-1.20	1.80
	1C1-097	2.00	4.04
	1C3-064	1.59	4.21
	1C3-075	1.64	1.83
Twin Lakes	Lower	1.08	1.57
	Upper	1.16	1.71

Note: The ratios of the means for alkalinity may not be representative of the system because the value of alkalinity can be negative. Therefore, negative ratios are also possible.

TABLE 3-5. REGIONAL MAXIMUM TO MINIMUM RATIOS OF QUARTERLY MEANS AND STANDARD DEVIATIONS FOR SULFATE

Region	Lake	Mean	Stand. Dev.
NLS-1A	Overall	1.14	2.03
	1A1-071	1.01	2.85
	1A1-087	1.66	3.05
	1A1-102	1.16	2.23
	1A1-105	1.13	1.89
	1A1-106	1.09	1.80
	1A1-107	1.16	3.20
	1A1-109	1.08	3.07
	1A1-110	1.11	5.18
	1A2-077	1.14	3.27
	1A2-078	1.20	2.81
NLS-1C	Overall	1.19	1.13
	1C1-091	1.20	2.23
	1C1-093	1.20	1.98
	1C1-097	1.06	2.28
	1C3-064	1.21	1.47
	1C3-075	1.30	4.00

TABLE 3-6. REGIONAL MAXIMUM TO MINIMUM RATIOS OF QUARTERLY MEANS AND STANDARD DEVIATIONS FOR pH

Region	Lake	Mean	Stand. Dev.
NLS-1A	Overall	1.09	1.58
	1A1-071	1.07	4.02
	1A1-087	1.15	1.73
	1A1-102	1.07	4.37
	1A1-105	1.11	2.70
	1A1-106	1.09	2.21
	1A1-107	1.04	2.55
	1A1-109	1.13	9.91
	1A1-110	1.16	2.39
	1A2-077	1.07	2.93
	1A2-078	1.18	2.81
NLS-1C	Overall	1.06	1.45
	1C1-091	1.13	6.71
	1C1-093	1.06	2.34
	1C1-097	1.08	4.43
	1C3-064	1.08	1.80
	1C3-075	1.07	4.00
Twin Lakes	Lower	1.03	3.62
	Upper	1.05	1.70

TABLE 3-7. SIGNIFICANT SKEW VALUES OF THE BEST DATA SETS FOR ALKALINITY

Region	Level	Raw Data	Logarithmic Transform*	Quarterly Means Removed
NLS-1A	10%	2 / 10	4 / 5	2 / 10
	2%	1 / 10	3 / 5	0 / 10
NLS-1C	10%	1 / 5	0 / 4	1 / 5
	2%	0 / 5	0 / 4	0 / 5
Twin Lakes	10%	0 / 2	0 / 2	0 / 2
	2%	0 / 2	0 / 2	0 / 2
Overall	10%	3 / 17	4 / 11	4 / 17
	2%	1 / 17	3 / 11	3 / 17

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.
* Because of negative alkalinity values, logarithmic transformations could not be performed on some of the data sets.

TABLE 3-8. SIGNIFICANT SKEW VALUES OF THE BEST DATA SETS FOR SULFATE

Region	Level	Raw Data	Logarithmic Transform	Quarterly Means Removed
NLS-1A	10%	4 / 10	2 / 10	2 / 10
	2%	1 / 10	1 / 10	1 / 10
NLS-1C	10%	1 / 5	1 / 5	1 / 5
	2%	1 / 5	1 / 5	1 / 5
Overall	10%	5 / 15	3 / 15	3 / 15
	2%	2 / 15	2 / 15	2 / 15

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.

TABLE 3-9. SIGNIFICANT SKEW VALUES OF THE BEST DATA SETS FOR pH

Region	Level	Raw Data	Logarithmic Transform	Quarterly Means Removed
NLS-1A	10%	2 / 10	2 / 10	0 / 10
	2%	1 / 10	1 / 10	0 / 10
NLS-1C	10%	1 / 5	1 / 5	1 / 5
	2%	1 / 5	1 / 5	1 / 5
Twin Lakes	10%	0 / 2	0 / 2	0 / 2
	2%	0 / 2	0 / 2	0 / 2
Overall	10%	3 / 17	3 / 17	1 / 17
	2%	2 / 17	2 / 17	1 / 17

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.

TABLE 3-10. SIGNIFICANT KURTOSIS VALUES OF THE BEST DATA SETS FOR ALKALINITY

Region	Level	Raw Data	Logarithmic Transform*	Quarterly Means Removed
NLS-1A	10%	2 / 10	4 / 5	3 / 10
	2%	1 / 10	3 / 5	1 / 10
NLS-1C	10%	1 / 5	1 / 4	1 / 5
	2%	0 / 5	0 / 4	0 / 5
Twin Lakes	10%	0 / 2	0 / 2	0 / 2
	2%	0 / 2	0 / 2	0 / 2
Overall	10%	3 / 17	5 / 11	4 / 17
	2%	1 / 17	3 / 11	1 / 17

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.

* Because of negative alkalinity values, logarithmic transformations could not be performed on some of the data sets.

TABLE 3-11. SIGNIFICANT KURTOSIS VALUES OF THE BEST DATA SETS FOR SULFATE

Region	Level	Raw Data	Logarithmic Transform	Quarterly Means Removed
NLS-1A	10%	3 / 10	2 / 10	2 / 10
	2%	0 / 10	0 / 10	0 / 10
NLS-1C	10%	1 / 5	1 / 5	1 / 5
	2%	1 / 5	1 / 5	1 / 5
Overall	10%	4 / 15	3 / 15	3 / 15
	2%	1 / 15	1 / 15	1 / 15

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.

TABLE 3-12. SIGNIFICANT KURTOSIS VALUES OF THE BEST DATA SETS FOR pH

Region	Level	Raw Data	Logarithmic Transform*	Quarterly Means Removed
NLS-1A	10%	2 / 10	2 / 10	3 / 10
	2%	1 / 10	2 / 10	1 / 10
NLS-1C	10%	1 / 5	1 / 5	1 / 5
	2%	1 / 5	0 / 5	0 / 5
Twin Lakes	10%	0 / 2	0 / 2	0 / 2
	2%	0 / 2	0 / 2	0 / 2
Overall	10%	3 / 17	3 / 17	4 / 17
	2%	2 / 17	2 / 17	1 / 17

Note: The format of the table is (# significant values / # total observations), therefore 2 / 10 means that 2 of the 10 data sets tested were significantly skewed at that particular level.

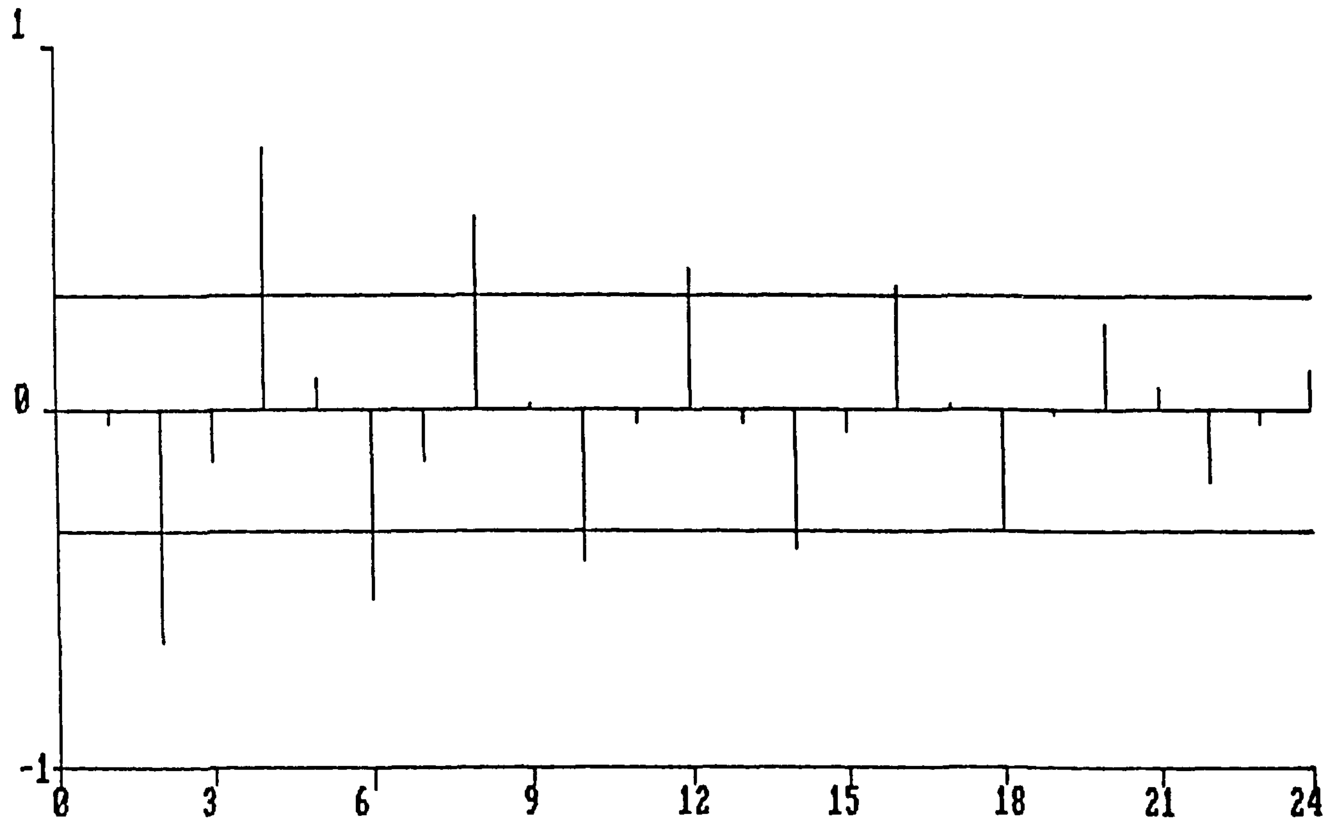


Figure 3-5. Correlogram for conductivity at Upper Twin Lake, Colorado--quarterly sampling, raw data.

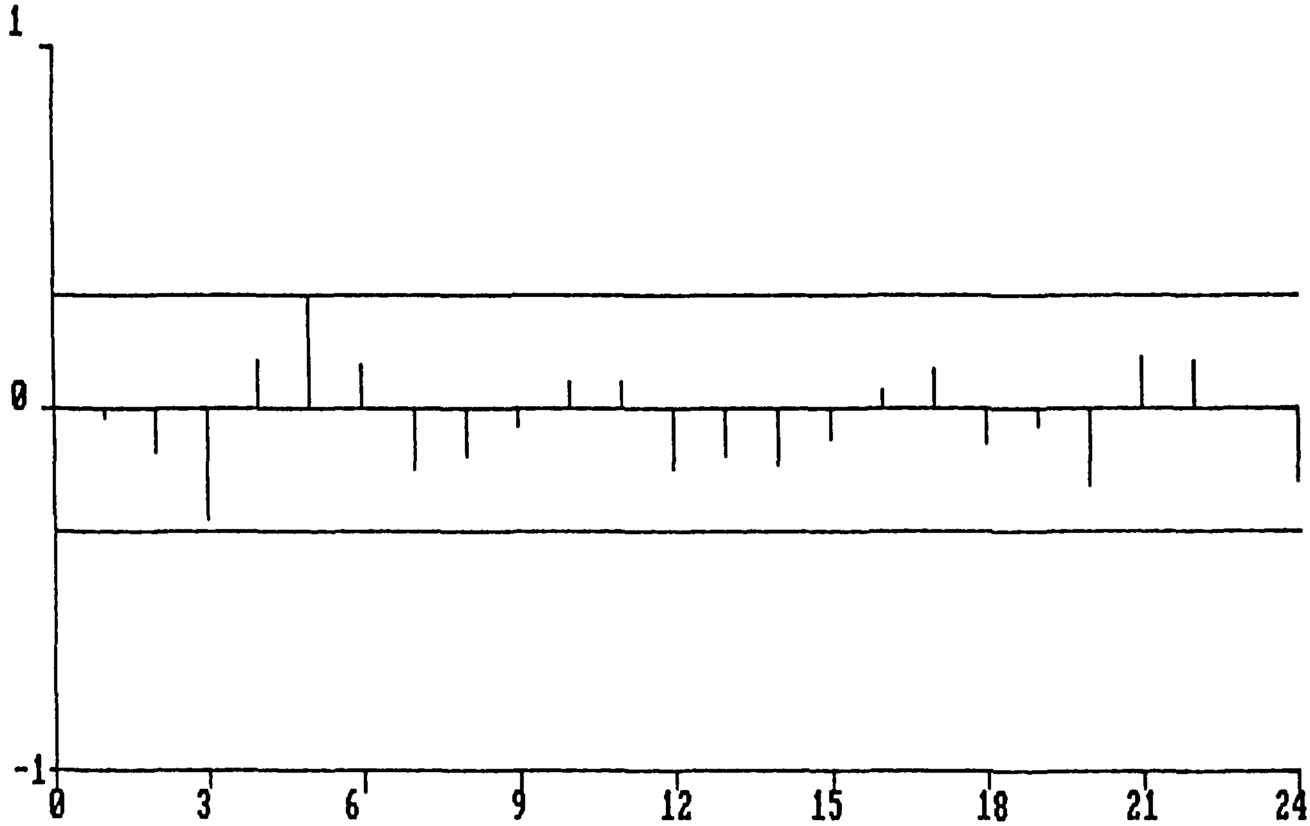


Figure 3-6. Correlogram for conductivity at Upper Twin Lake, Colorado--quarterly sampling, seasonal means removed.

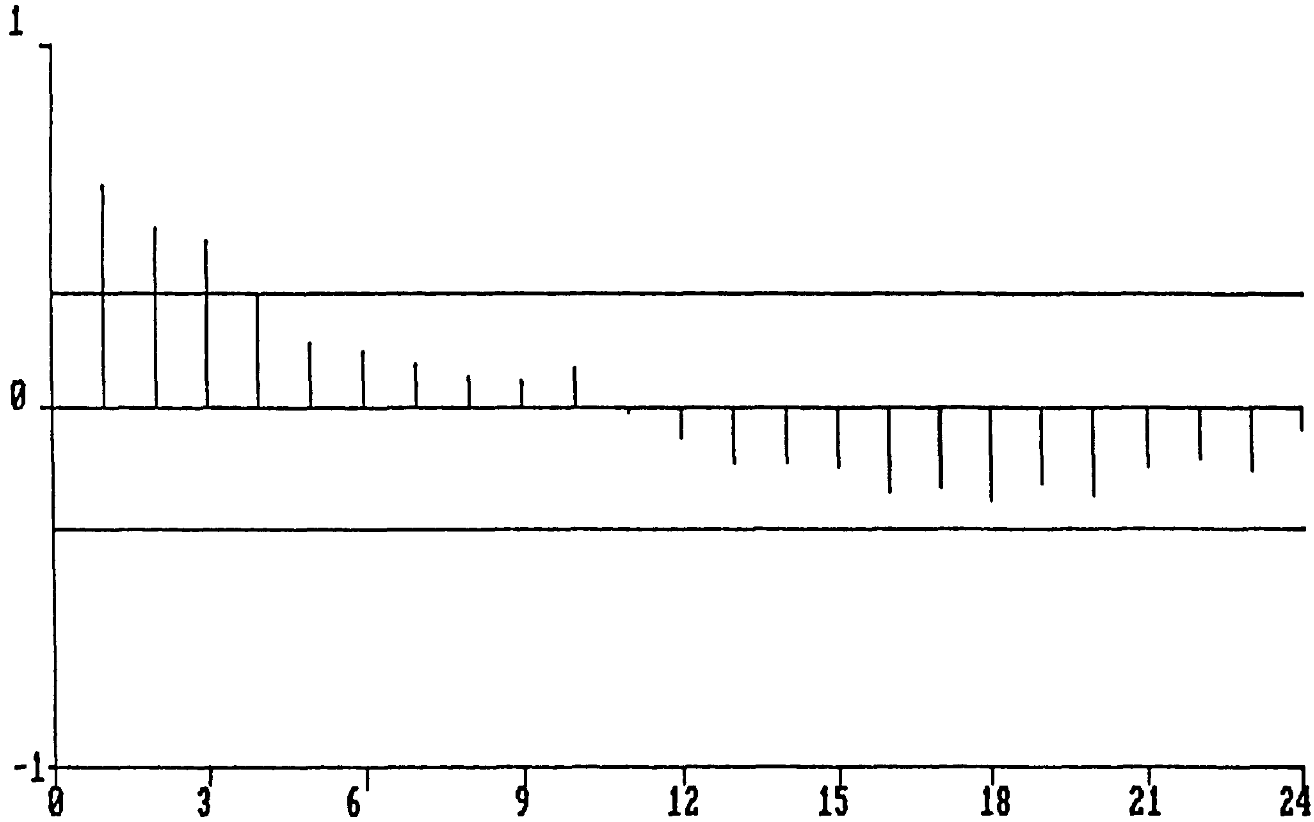


Figure 3-7. Correlogram for conductivity at Lower Twin Lake, Colorado--quarterly sampling, raw data.

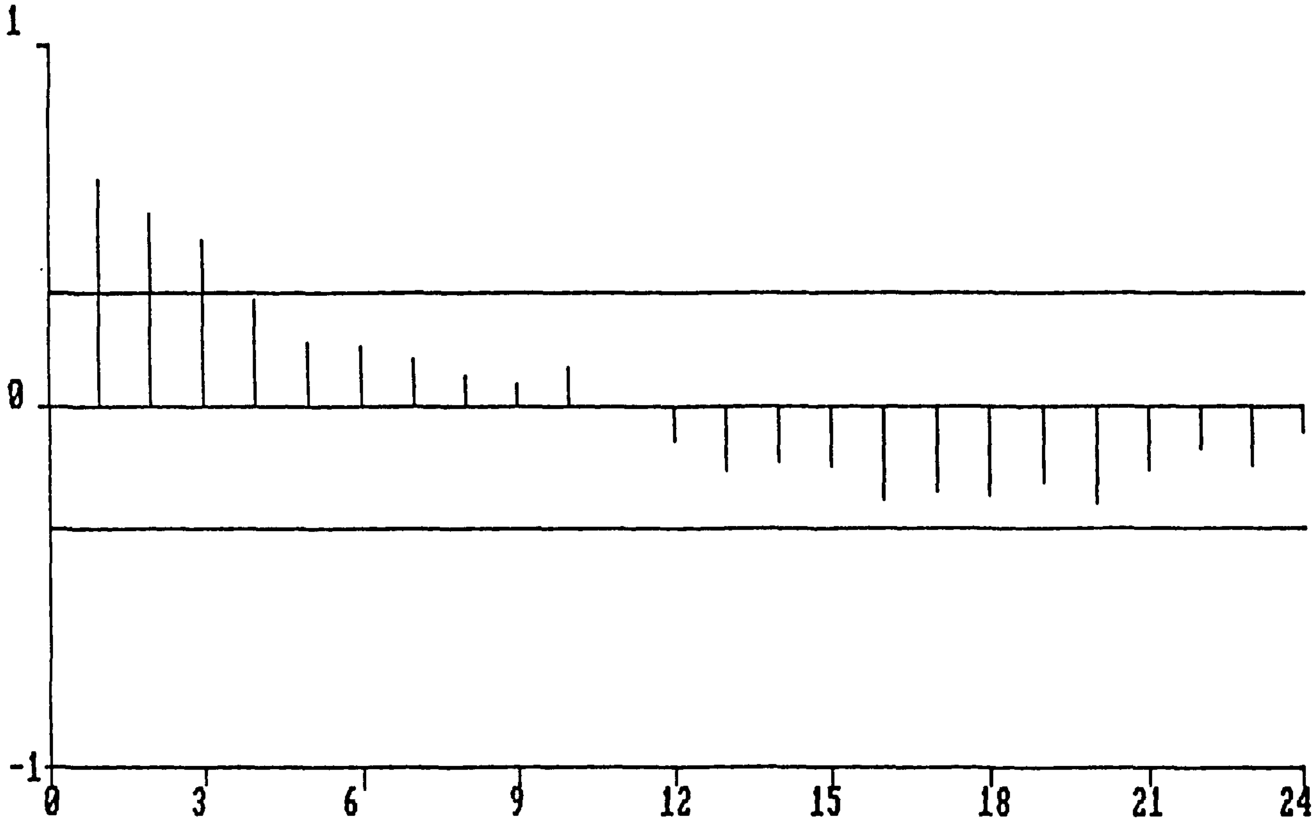


Figure 3-8. Correlogram for conductivity at Lower Twin Lake, Colorado--quarterly sampling, seasonal means removed.

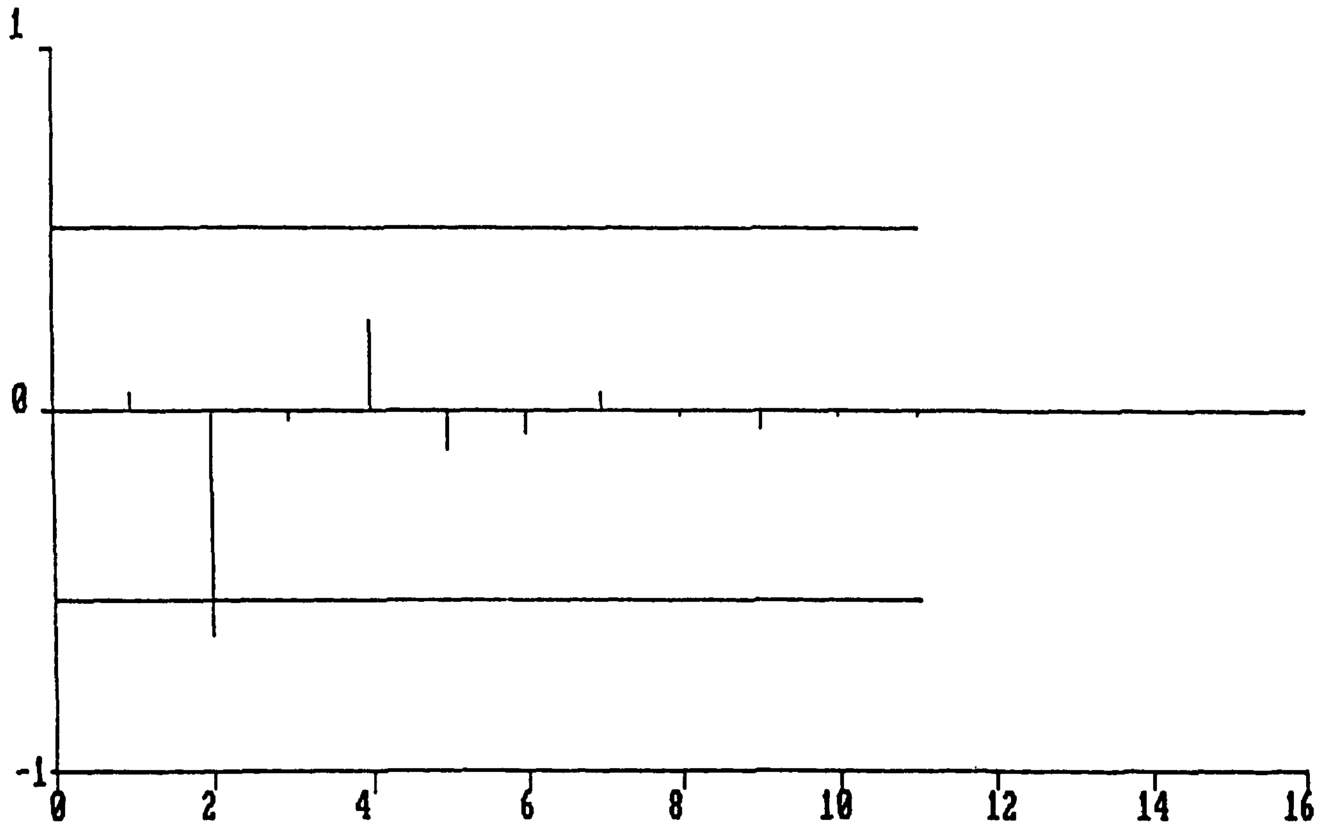


Figure 3-9. Correlogram for alkalinity at Lake 1A1-105, quarterly sampling, raw data.

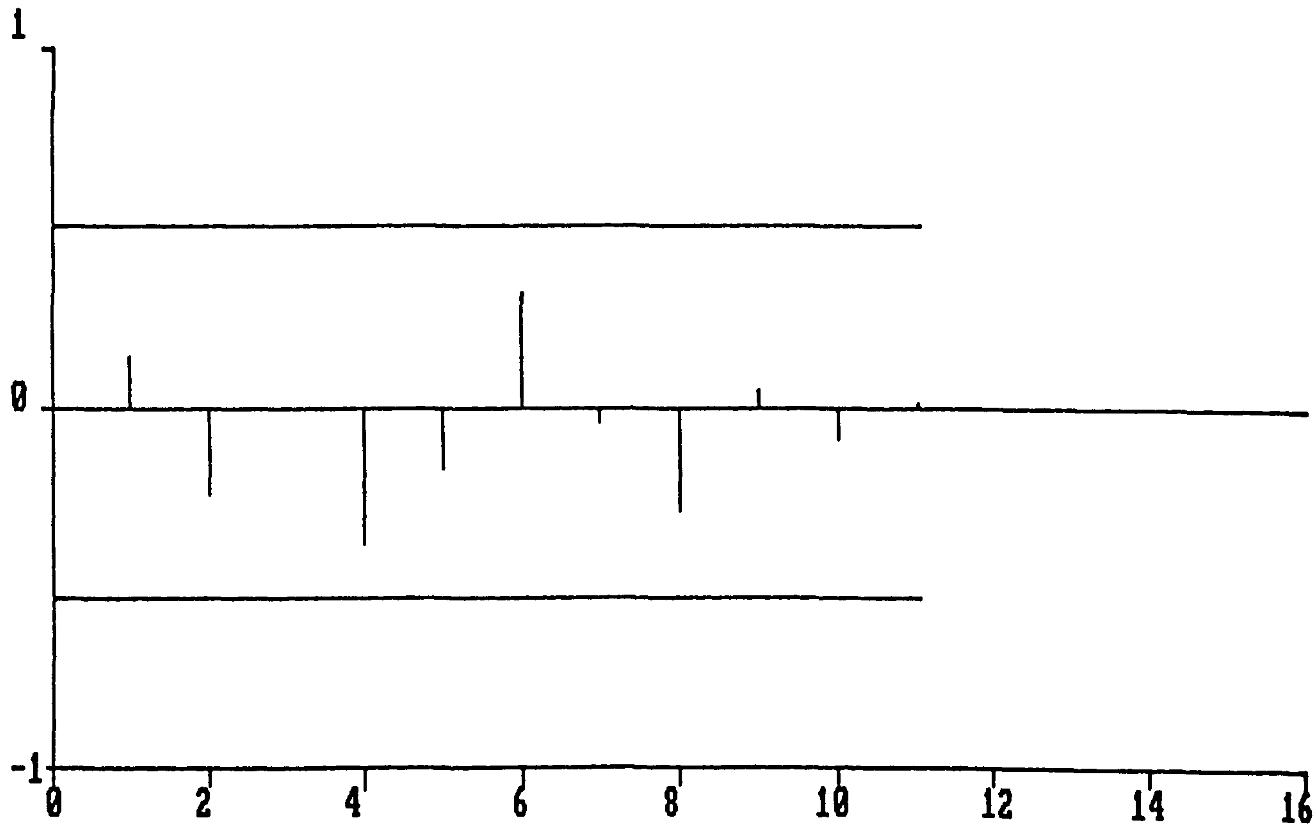


Figure 3-10. Correlogram for alkalinity at Lake 1A1-105, quarterly sampling, seasonal means removed.

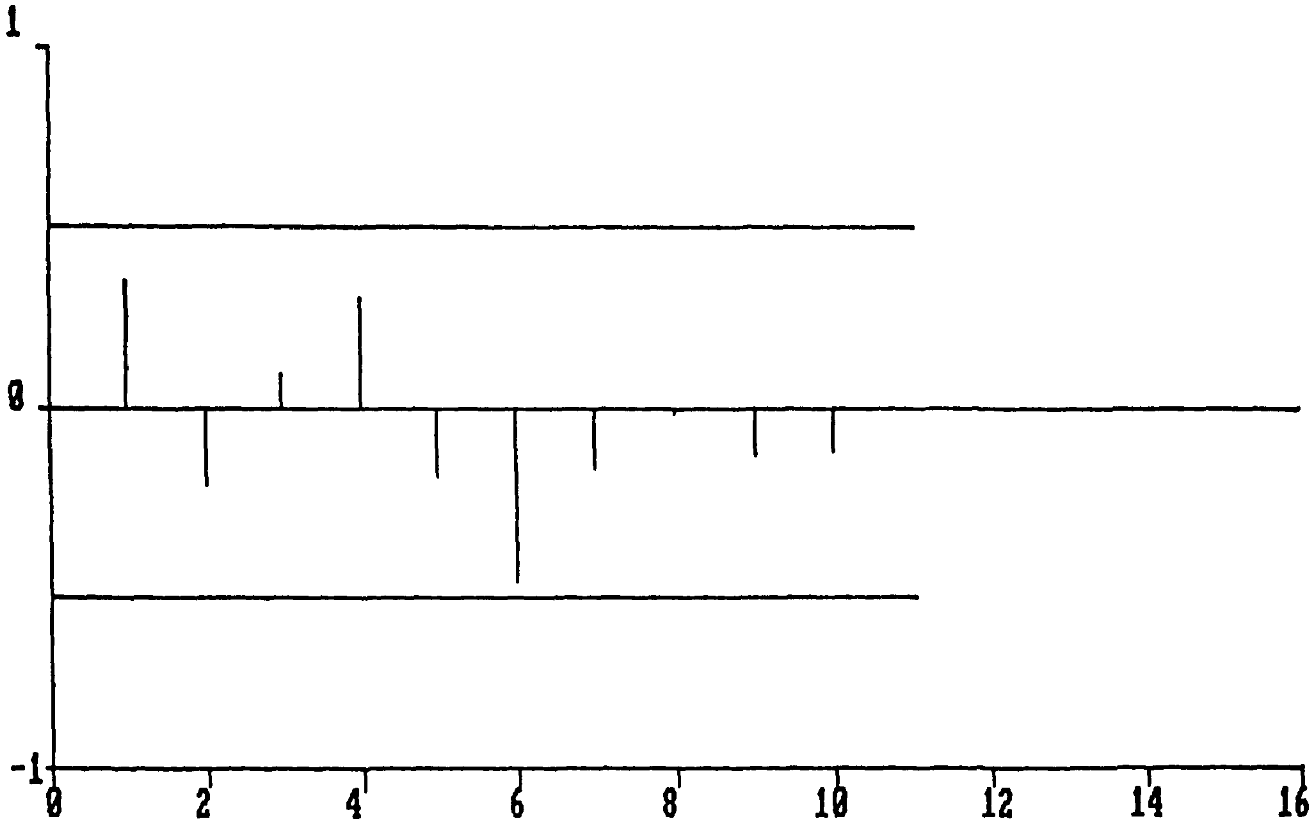


Figure 3-11. Correlogram for alkalinity, Lake 1A1-102, quarterly sampling, raw data.

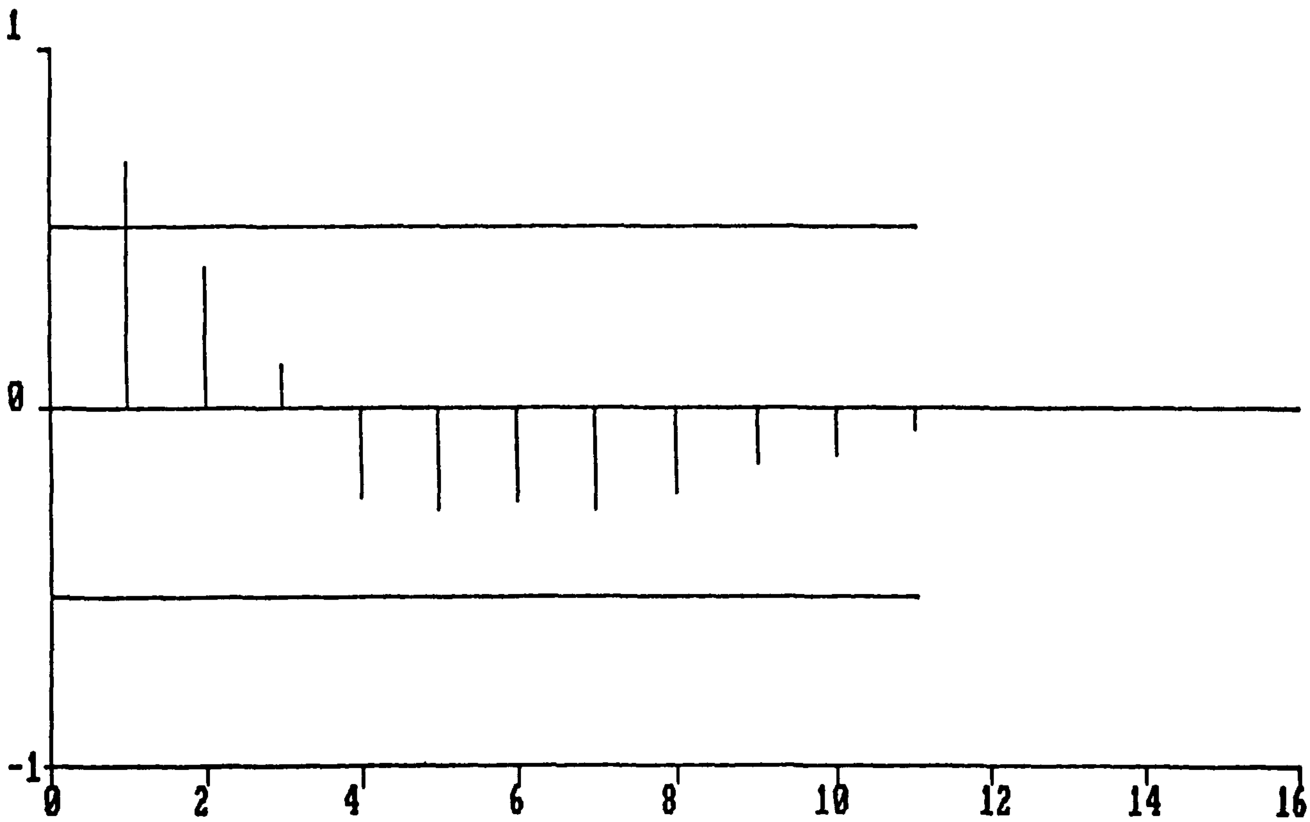


Figure 3-12. Correlogram for alkalinity, Lake 1A1-102, quarterly sampling, seasonal means removed.

The vertical lines represent the amount of correlation r(k) for each lag, k. If any of the vertical lines cross either of the two outer horizontal lines, then correlation at that lag is statistically significant at the 95% level. Significant values of the correlogram can result from seasonality, serial correlation, or trend. The probability that a significant value results from random chance is less than 5%. The correlation between one observation and the next is represented by r(1). For a trend free series, a significant lag 1 correlation and a decay for lags following represents serial correlation.

The value of r(2) is the correlation between every second observation. For quarterly data, this would be the correlation between adjacent springs and falls, and summers and winters. Lag 4 would then be the correlation between every fourth observation, or annual correlation for quarterly data. A periodic cycle of a negative lag 2, a positive lag 4, a negative lag 6, and so on indicates an annual seasonal cycle within the data set.

If the correlogram of the raw data shows an annual cycle and the correlogram of data with quarterly means removed shows steady decay, we would conclude that both seasonality and serial correlation are present.

Figure 3-5, depicting conductivity at Upper Twin Lake, Site 4, shows a dramatic annual cycle. In Figure 3-6, the quarterly means have been removed, and we are left with an uncorrelated series. Figure 3-7 is a correlogram for conductivity at Lower Twin Lakes, Site 2. Seasonality is not apparent, but serial correlation is significant. As we would expect, removing the quarterly means does not greatly affect the correlogram (Figure 3-8). Figure 3-9, depicting alkalinity at NLS-1A Lake 1A1-105 is based on a smaller data set and shows significant but less dramatic seasonality. Removing quarterly means (Figure 3-10) produces a series with no significant serial correlation. For Lake 1A1-102, the alkalinity correlogram (Figure 3-11) shows no significant serial correlation, but apparent seasonality is present. Removing quarterly means reveals significant serial correlation of the residual series (Figure 3-12).

Tables 3-13 through 3-16 list the number of lakes (by region and variable) that showed significant serial correlation of various types.

3.3 ALTERNATE METHODS FOR TREND ANALYSIS

Seven statistical tests for trend were selected as candidates for evaluation and possible use within TIME. The selection was based on the results of background data characterization and on a review of the statistical and hydrological literature. The candidate procedures were as follows:

a. Analysis of covariance (ANOCOV) on raw data
b. Modified "t" on raw data
c. Kendall tau on deseasonalized data (also called the Kendall Rank Correlation test or Mann-Kendall test for trend)
d. Seasonal Kendall with correction for serial correlation
e. Seasonal Kendall
f. Analysis of covariance (ANOCOV) on ranks of data
g. Modified "t" on ranks of data

A brief discussion of these procedures follows. A detailed description of the tests is presented in Section 6.

TABLE 3-13. SIGNIFICANT CORRELATIONS OF THE BEST DATA SETS FOR ALKALINITY

Region	Number Lakes	Raw Data Significant Lag 1	Detectable Seasonality	Significant Seasonality	Deseason. Significant Lag 1
NLS-1A	10	0	9	4	3
NLS-1C	5	0	4	2	1
Twin Lakes	2	2	0	0	2
Overall	17	2	13	6	6

TABLE 3-14. SIGNIFICANT CORRELATIONS OF THE BEST DATA SETS FOR SULFATE

Region	Number Lakes	Raw Data Significant Lag 1	Detectable Seasonality	Significant Seasonality	Deseason. Significant Lag 1
NLS-1A	10	0	6	2	1
NLS-1C	5	0	3	1	1
Overall	15	0	9	3	2

TABLE 3-15. SIGNIFICANT CORRELATIONS OF THE BEST DATA SETS FOR pH

Region	Number Lakes	Raw Data Significant Lag 1	Detectable Seasonality	Significant Seasonality	Deseason. Significant Lag 1
NLS-1A	10	0	9	4	0
NLS-1C	5	2	2	1	1
Twin Lakes	2	0	1	1	1
Overall	17	2	12	6	2

TABLE 3-16. SIGNIFICANT CORRELATIONS OF THE BEST DATA SETS FOR ALL VARIABLES

Region	Number Lakes	Raw Data Significant Lag 1	Detectable Seasonality	Significant Seasonality	Deseason. Significant Lag 1
NLS-1A	30	0	24	10	4
NLS-1C	15	2	9	4	3
Twin Lakes	4	2	1	1	3
Overall	49	4	34	15	10

Analysis of covariance (ANOCOV) is based on a linear model and normal theory (Neter and Wasserman, 1974). The trend test is simply multiple linear regression of a water quality (dependent) variable against two or more predictive (independent) variables. One of the dependent variables is time, and the rest are seasonal indicator variables. For quarterly observations, three indicator variables are used, corresponding to any three of the four seasons--for example, winter, spring, and summer. To indicate a winter observation, the first indicator variable would be set equal to one and the rest equal to zero. For spring observations, the second indicator variable would equal one, the rest zero. If all three indicator variables are zero, a fall observation is indicated.

The regression calculates three seasonal or coefficent terms, an overall intercept, and a slope against time. The slope against time is tested for significance using a null hypothesis that the slope is zero. If the null hypothesis is rejected, we conclude that there is a significant (linear) trend in the data.

The ANOCOV procedure assumes homogeneous (constant) variance across all seasons. Since TIME data are expected to exhibit seasonal changes in variance, however, another test was developed that does not assume homogeneous variance. This test, called the modified "t", involves a separate linear regression of the water quality variable against time in each season. The regressions are followed by a test of the null hypothesis that the sum of the regression slopes (four slopes for quarterly data) is equal to zero. If all slopes are assumed to be in the same direction, this condition is satisfied only if there is not overall (linear) trend. If the null hypothesis is rejected, we conclude that there is a significant overall linear trend.

The Kendall-tau procedure is described in Snedecor and Cochran (1980). The method is nonparametric, meaning that it does not depend on an assumption of a particular underlying distribution. The procedure tests for correlation between the ranks of data and time, and as noted by Gilbert (1987), "can be viewed as a nonparametric test for zero slope of the linear regression of time-ordered data versus time, as illustrated by Hollander and Wolfe (1973, p. 201)." Since the test depends only on relative magnitudes of data rather than actual values, it may also be viewed as a test for general monotonic trends rather than specifically linear trends.

Seasonal variation should be removed from a data series prior to the application of this test. This is accomplished by computing seasonal means (for example, the sample mean of all fall values) and subtracting the appropriate seasonal mean from each observation. The procedure utilized herein is to subtract seasonal means without any prior test for seasonality. In other words, all data series are assumed to be seasonal and are "deseasonalized" prior to applying Kendall-tau. Of course, for annual data in which all observations are from the same time of year, the "deseasonalizing" step is not necessary.

The seasonal Kendall test as described in Hirsch et al. (1982) is an extension of the Kendall-tau test. The seasonal Kendall test statistic is the sum of Kendall-tau statistics computed for each season (month or quarter, for example) of the year. This test accounts for seasonal variation directly and does not require prior removal of seasonal means.

The sixth and seventh procedures are identical to the first and second with one exception. The data are first ranked, and the ranks are substituted for the original values of the observations. The rank transformation is suggested by Conover (1980). The fourth and fifth procedures are identical with one exception. In the fourth procedure, the variance of the seasonal Kendall test statistic is corrected by including a covariance term which reflects serial correlation of observations. The modification is described in Hirsch and Slack (1984).

Two key assumptions of the various tests should be emphasized at this point. First is the form of trend assumed. The analysis of covariance model assumes a linear trend component, and the modified "t" assumes a linear trend within each season. Although the tests are certainly appropriate for more general trends (gradually increasing or decreasing but not necessarily in a straight line), keep in mind that our comparisons were based on linear trend. Thus they slightly favored these two tests. The ANOCOV and modified "t" on ranks make the same assumptions, but on the ranks of data rather than the actual observations. Thus linear trends in the observations are not assumed, but we do assume that the form of the trend is gradually increasing or decreasing. The Kendall tau and seasonal Kendall tests are designed for general monotonic trend. Thus they would be regarded as more general than the other tests.

In fact any of the tests could be applied to a wide variety of trend shapes, including quadratic or step trends. If trends are not monotonic, meaning that the general tendency is in one direction for a while and then the reverse, the tests would not be very sensitive, unless there was a clear overall tendency in one direction or the other. Thus, we would generally want to inspect time series plots before performing the tests, to identify segments with differing trend directions or other characteristics indicating that more in-depth treatment is necessary.

The second key assumption is independence of observations. All of the tests account for seasonal dependence in some way or other; however, only the corrected seasonal Kendall test accounts for serial correlation--temporal dependence after seasonality is removed. All of the other tests assume that samples are independent in the absence of seasonality, meaning that there is not serial correlation.

Although we do not believe that quarterly observations will exhibit strong levels of serial correlation, it should be understood that any serial correlation will affect the performance of the tests. The tests will tend to reject the null hypothesis more often than they should. The correlated series will tend to drift above or below the long-term mean and stay there for a while, and this drift will sometimes be indistinguishable from trend, depending on the time horizon over which the process is viewed. (The term "drift" has a particular connotation in stochastic modeling, which is not intended here.)

In practice, the classification of observed patterns as either trend or serial correlation is rather subjective. There is no way to overcome this difficulty without very long records or physical explanations for observed patterns. Thus we have not spent a great deal of time working on methods to account for serial correlation in trend analysis. More discussion of the issue appears in the section 3.4 on the results of Monte Carlo evaluation of candidate tests.

3.4 MONTE CARLO EVALUATION OF CANDIDATE TESTS

Since analytical evaluations of power and significance levels are possible only in a limited number of situations, a good comparison of trend testing methods is best achieved through Monte Carlo testing. In a Monte Carlo evaluation, the significance level of a test is determined by generating a large number (e.g., 500) of sequences of data with known characteristics and no trend. The test is applied to each sequence, and the significance level is the fraction of trials in which a trend is falsely detected. The power of a given test is determined in the same way, except that a trend of known magnitude is added to each synthetic data sequence. The power is the fraction of sequences in which the trend is correctly detected.

To compare alternative tests, we need to perform a very large number of simulation experiments. Time series of several types must be considered. To adequately represent the range of characteristics anticipated from TIME data, the parameters that should be varied are magnitude of seasonality in mean, pattern of seasonality in mean, magnitude and pattern of seasonality in variance, normal versus non-normal distribution, degree of serial correlation, trend magnitude, and length of record. The number of possible combinations of these parameters is very large, and rigorous testing of all possibilities would require an enormous amount of computer time.

Therefore, we developed a limited Monte Carlo testing program that examined a few key values of the above parameters, based on our historical data analysis, and tried all possible combinations thereof. The simulations are described in Table 3-17. Only normal and lognormal distributions were considered, and only simple AR(1) type autocorrelation was considered. Autocorrelation was not considered for the lognormal case. Even with these simplifications, 3,024 combinations of parameters were evaluated. For each combination, at least 500 sequences were generated to empirically determine the power or significance level of the candidate tests. Details of the synthetic data generation procedure are presented in Section 6. All candidate tests were applied to each synthetic data sequence.

3.5 RESULTS OF MONTE CARLO EVALUATION

Summary results of the Monte Carlo evaluation are presented in Tables 6-1 through 6-4 in Section 6, along with a more complete discussion. Complete results are presented in Appendix B, Tables B-1 through B-6. Briefly, the most powerful tests over the range of conditions studied appear to be the seasonal Kendall test and ANOCOV on ranks, although as expected, no single test performs best under all conditions. Both of these tests performed as well as the parametric tests when the data were normal and both out-performed (were more powerful than) the parametric tests when the underlying distribution was lognormal. In a few cases, the Kendall-tau on deseasonalized data was more powerful, but it did not generally preserve the nominal significance level as well as the other tests. The modified "t" test on ranks performed well, but was in most cases slightly less powerful than ANOCOV on ranks.

All tests except the corrected seasonal Kendall (d) suffered from inflated significance levels under serial correlation. The corrected test, however, is much less powerful than the other tests, except for very large trend magnitudes and/or long data records. As expected, it is very *difficult to distinguish between linear trend and serial correlation.*

The corrected seasonal Kendall test is not recommended for routine application by TIME until very long records (say 15-20 years of quarterly data) have been obtained. The correction for serial correlation will cause the test to ignore trends of moderate magnitude and duration that may be important from a management standpoint. The question of whether a change in water quality is of interest is one of physical causality. Persistence in the series, as described by a correlated process model, could be caused by some factors that are not of interest (e.g., long lake retention time) and others that are of interest (e.g., cycles of industrial activity). We argue that it is wiser to detect more trends, some of which are false positives, and then to screen according to probable cause, than to overlook changes that are really of interest.

In fact, we believe that it will probably not be possible to deal satisfactorily with the issue of serial correlation with any routine time series approach until very long records are available. Although several methods are available, such as ARIMA modeling of the time series and extensions of linear regression, all require some type of estimation of the correlation structure of the series of interest. The trend test is then modified in some way to account for the correlation.

In particular, the distribution of a test statistic will be obtained under a null hypothesis of no deterministic trend plus some (estimated) serial correlation structure. The distribution of the test statistic, under the null hypothesis, will depend on the true correlation structure. However, the rejection value must depend on the estimated structure. Even if the true correlation structure were known exactly, the variance of the test statistic under the null hypothesis would be increased (compared to the uncorrelated case), resulting in lower power. Also, for small to moderate sample sizes, the estimated parameters of the correlation structure will have a high variance, making matters ever worse. For example, assuming an AR(1) structure, the variance of

TABLE 3-17. DESCRIPTION OF SIMULATIONS FOR MONTE CARLO TESTING PROGRAM

A. Seasonal patterns in mean

Pattern (1)	Quarter 1 - Low
	Quarter 2 - High
	Quarter 3 - Low
	Quarter 4 - Low
Pattern (2)	Quarter 1 - Low
	Quarter 2 - High
	Quarter 3 - Low
	Quarter 4 - High

B. Seasonal patterns in standard deviation

(same two patterns as in mean)

C. Ratios of largest to smallest quarterly standard deviation

1.0, 1.5, 3.0, 5.0

D. Ratio of largest to smallest quarterly mean

1.0, 1.5, 2.0

E. $$\text{Trend magnitude} = \frac{\text{(change in mean per sampling interval)}}{\text{(average standard deviation over all quarters)}}$$

0.0, 0.002, 0.005, 0.02, 0.05, 0.2, 0.5

F. Length of record (years)

5, 15, 25

G. Underlying distribution

Normal, log normal

H. Lag-one autocorrelation coefficient $\rho(1)$ =

0.2, 0.4
(Correlated sequences generated for normal data only.)

I. Nominal significance level = 0.05 for all tests.

r(1), the sample estimate of $\rho(1)$, is approximately equal to $(1-\rho(1)^2)/n$. If $\rho(1) = 0.2$, and $n = 24$ (6 years of quarterly data), then the standard deviation of r(1) would be about 0.2--the same magnitude as the true value of $\rho(1)$.

In simpler terms, there is no way to uniquely characterize a correlated time series with small sample sizes. For large sample sizes, more complex time series methods may be justified. In the case of TIME, we have about 20 years to work on the problem.

In the meantime, we feel that other avenues, involving the development of closer links between statistical and physical models of the system, offer greater promise of an effective solution to the serial correlation problem. Statistical correlation should be due to physical factors, such as multi-year weather patterns. Consequently, it should be possible to replace a stochastic model of serial correlation structure with more physically based models, ranging from multivariate linear models with additional predictive variables to detailed and complex watershed models. We hope that the more physically based models can be formulated and calibrated with intensive sampling over a shorter time frame, as opposed to sampling over a long period (> 20 years). These models also offer greater potential for transferability between watersheds than univariate time series models.

As stated earlier, the two recommended tests out of the seven candidates are ANOCOV on ranks and seasonal Kendall. ANOCOV on ranks offers the advantage of being insensitive to the pattern and magnitude of seasonal change in variance. It is also easily applied by anyone who has a microcomputer stat package with a multiple linear regression capability. ANOCOV is also a very flexible method. The general ANOCOV model and procedure can be expanded by adding covariates to achieve additional power or increased ability to explain trends. Additional discussion of this topic follows in Section 5.

On the other hand, the seasonal Kendall test has a proven track record in water quality data analysis (Smith et al., 1987) and offers slightly better performance under certain conditions, notably the presence of serial correlation. For these reasons, the authors have a slight preference for the seasonal Kendall test. We recommend including ANOCOV on ranks as an alternative because of its ease of application with statistical packages and its potential for extension to multivariate tests. A further comparison of the two tests under alternate models of seasonality is presented in Section 6.

SECTION 4
EXPECTED PERFORMANCE OF MONITORING--POWER OF TREND DETECTION

The actual ability of TIME monitoring and data analysis to detect trends in water quality will depend upon data characteristics, especially temporal variance, and upon the shape or functional form and magnitude of the trend that actually occurs. Thus trend detection powers cannot really be predicted in advance. It is informative, however, to assume a reasonable set of data characteristics and trend characteristics and then to calculate detectable trend magnitudes over various time horizons. Thus, the adequacy of a proposed monitoring network design can be evaluated in objective terms.

An assumption of linear trend is used for this entire report. Actual trends may not be linear; however, the type of trend anticipated from changing acidic deposition is one of fairly gradual change over several years, as opposed to an abrupt shift in a year or two. Likewise, only normal and lognormal underlying distributions are considered. Both logic and analysis of historical data dictate that other distributions will be encountered by TIME. However, these distributions have been proven to have fairly broad applicability for major ions, and can therefore serve as a basis for evaluating network performance in the design stage. Furthermore, the recommended trend testing methods are based on ranks of data and are thus insensitive to the form of underlying distribution.

4.1 INDIVIDUAL LAKES

Under idealized conditions of independent, identically distributed normal samples, linear trends in a time series may be detected using linear regression. Under these conditions, the power of the test for significance of the regression slope may be estimated as follows (Lettenmeier, 1976).

First, compute a dimensionless trend number N_t using

$$N_t = \frac{[n\ (n+1)\ (n-1)]^{1/2}T}{12^{1/2}\sigma}$$

where n = number of observations used in the regresssion
T = trend magnitude in units per sampling interval (for example (μeq L^{-1}) per quarter)
σ = standard deviation of the water quality variable in the absence of a trend.

Then, the power of the test is approximated by $1-\beta = F(N_t - t_{1-\alpha/2,\gamma})$, where F is the cumulative distribution function of the student's "t" distribution with γ = n-2 degrees of freedom.

Since the trend is linear, the total change in mean concentration occurring over n samples is nT. Under real-world conditions of seasonality, non-normality, and serial correlation, the power of the test will be different from that shown above. The simulation results reported in the previous section provide powers for certain sets of more realistic conditions.

Figures 4-1 through 4-4 depict the power of trend detection for each region for 4 different trend magnitudes (T/σ = 0.005, 0.02, 0.05, and 0.20 for quarterly observations, or 4 times these values for annual observations) over a 25-year time horizon. Each graph contains curves for quarterly sampling and annual sampling. The curves were developed using the equation discussed above for the power of the "t" test and linear regression.

POWER OF TREND DETECTION

For Trend = 0.005 Std. Dev. per Quarter

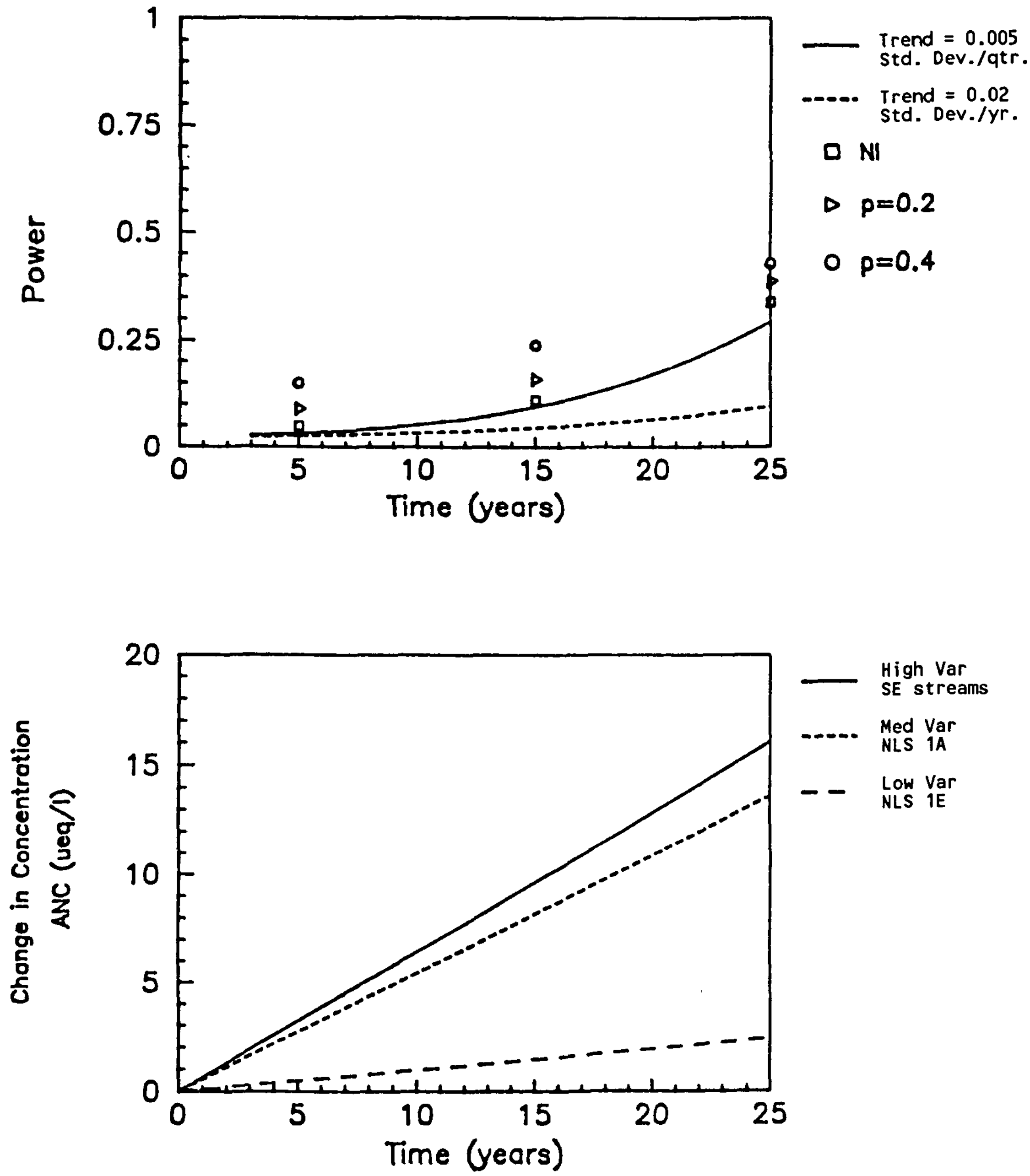
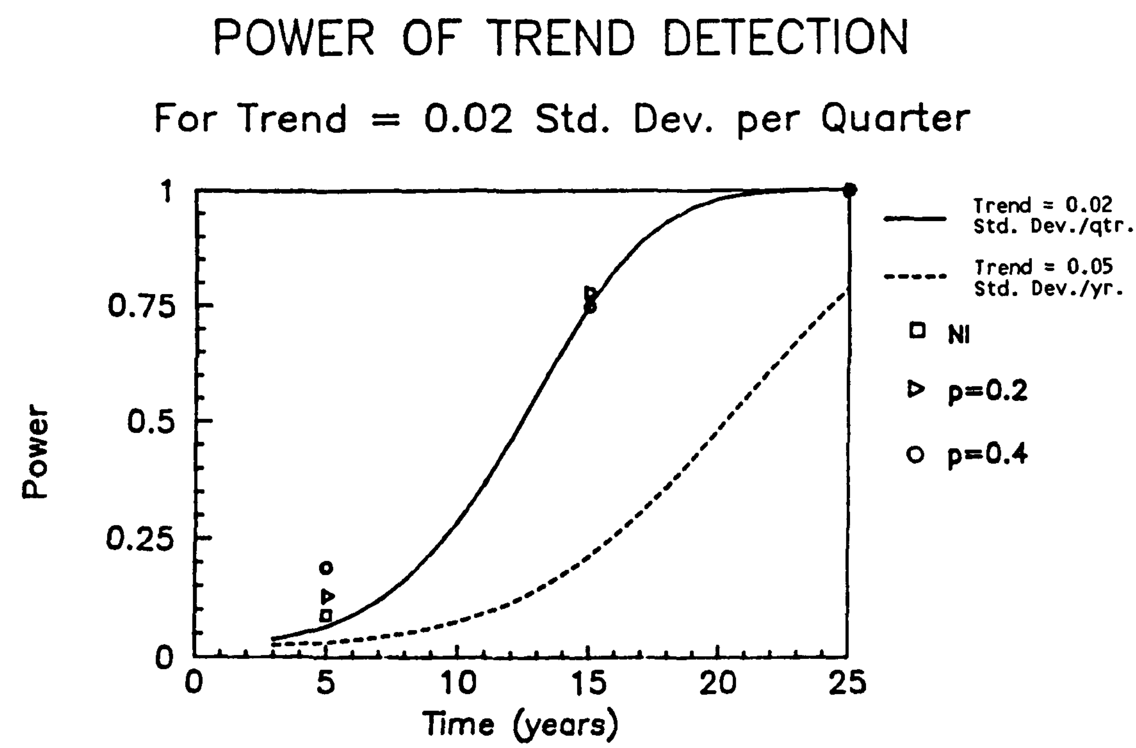


Figure 4-1. Power of trend detection for trend = 0.005 standard deviations per quarter and 0.02 standard deviations per year. The curves in the upper graph are the power calculated with the trend number. The points are the results from the simulation for ANOCOV on ranks for independent, rho = 0.2 and rho = 0.4 data, sampled quarterly. The lower graph shows the magnitude of the simulated trend at three levels of variability.



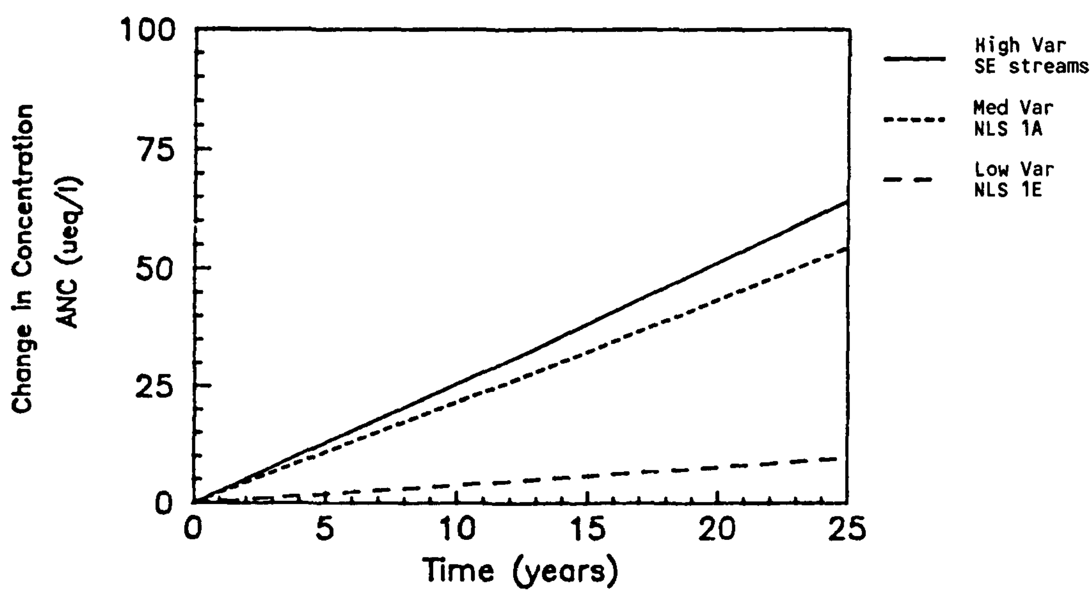
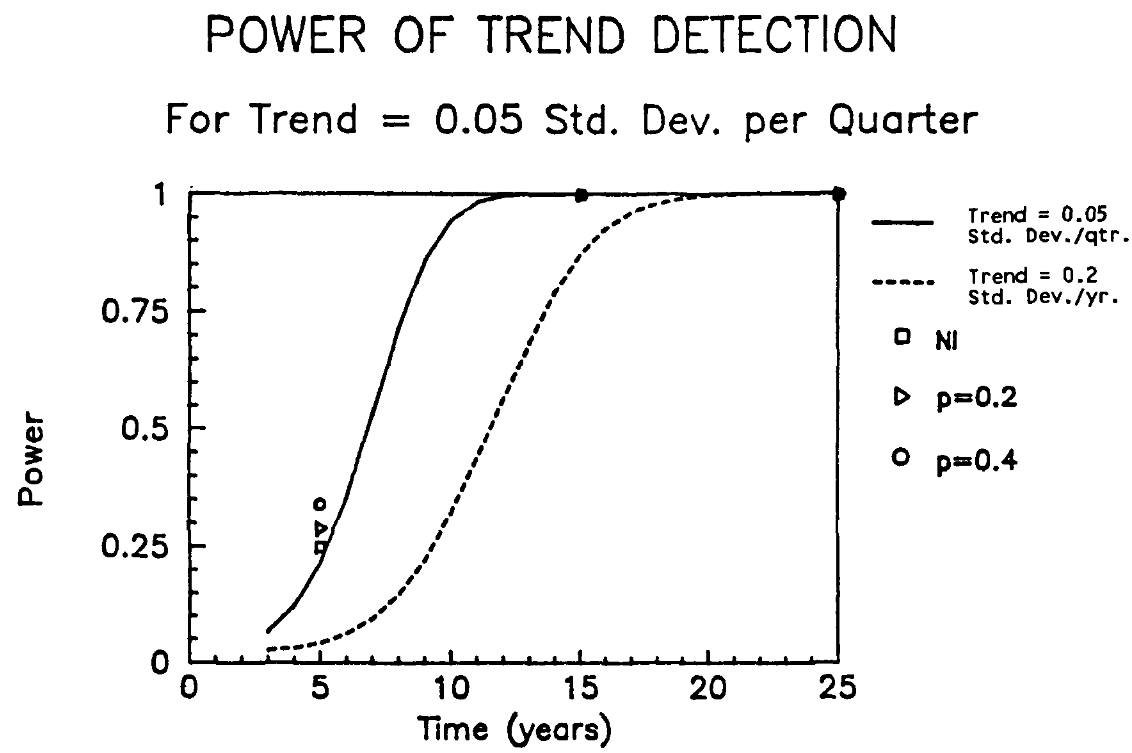


Figure 4-2. Power of trend detection for trend = 0.02 standard deviations per quarter and 0.08 standard deviations per year. The curves in the upper graph are the power calculated with the trend number. The points are the results from the simulation for ANOCOV on ranks for independent, rho = 0.2 and rho = 0.4 data, sampled quarterly. The lower graph shows the magnitude of the simulated trend at three levels of variability.



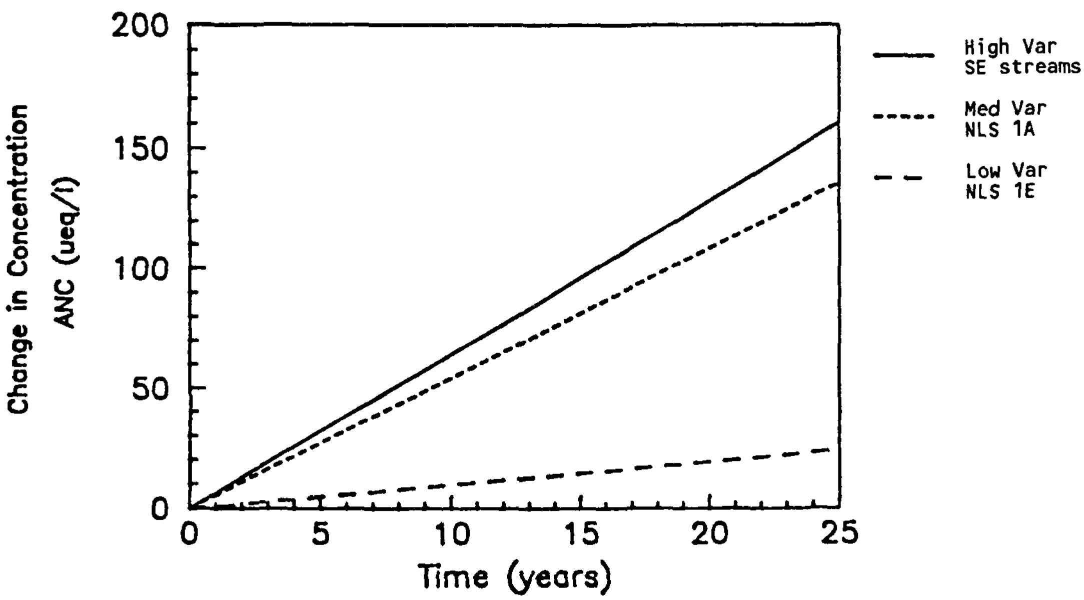
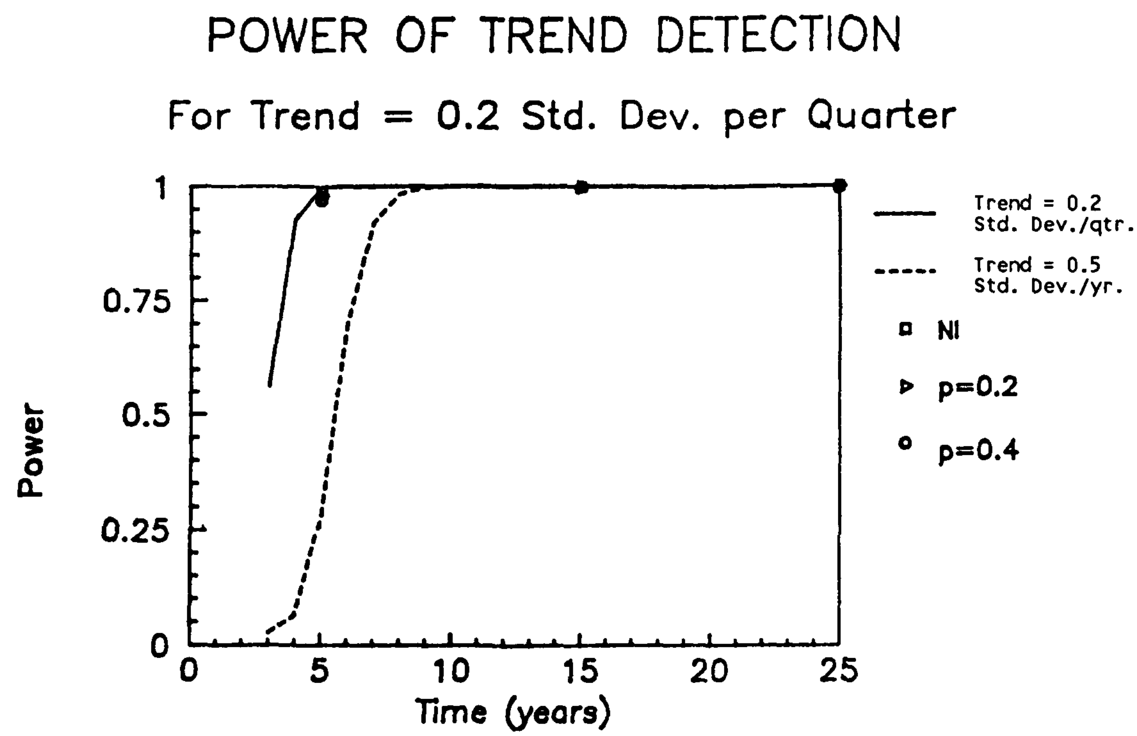


Figure 4-3. Power of trend detection for trend = 0.05 standard deviations per quarter and 0.20 standard deviations per year. The curves in the upper graph are the power calculated with the trend number. The points are the results from the simulation for ANOCOV ranks for independent, rho = 0.2 and rho = 0.4 data, sampled quarterly. The lower graph shows the magnitude of the simulated trend at three levels of variability.



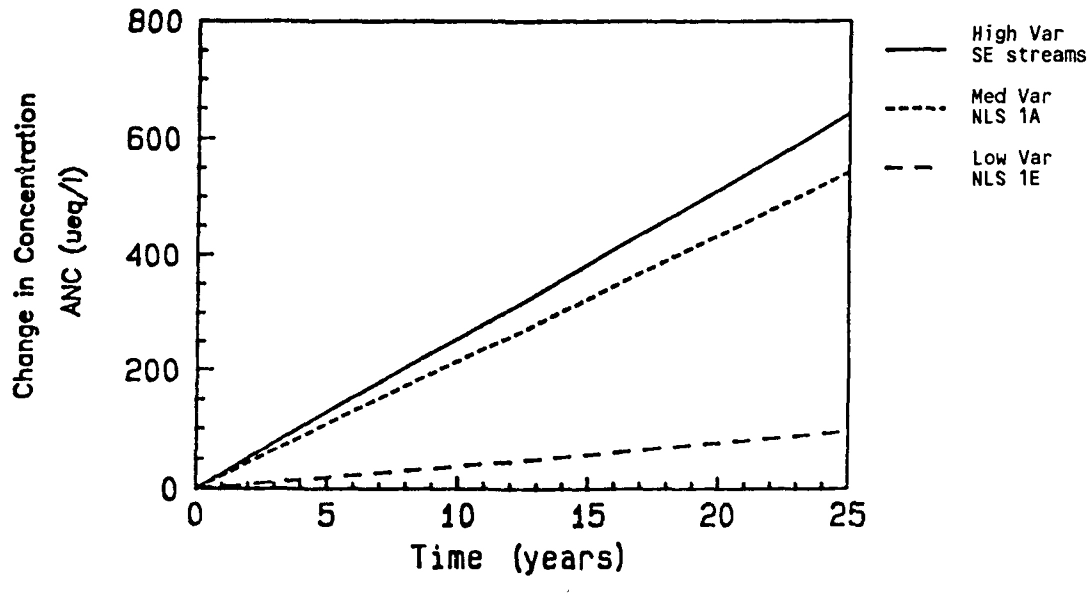


Figure 4-4. Power of trend detection for trend = 0.20 standard deviations per quarter and 0.8 standard deviations per year. The curves in the upper graph are the power calculated with the trend number. The points are the results from the simulation for ANOCOV on ranks for independent, rho = 0.2 and rho = 0.4 data, sampled quarterly. The lower graph shows the magnitude of the simulated trend at three levels of variability.

Anticipated powers under real-world conditions are shown as individual plotted points taken from the simulation results reported earlier for ANOCOV on ranks over the whole range of seasonality studied. Plotted points correspond to normal-independent, normal-$\rho(1) = 0.2$ and normal-$\rho(1) = 0.4$--all under quarterly sampling. Under annual sampling, seasonal variation and serial correlation are not important, and the theoretical curve should give an adequate representation of anticipated power. Powers for lognormal data are higher than those for normal data, are not directly comparable, and are therefore not included.

In both the idealized and real-world cases, the trend magnitude is expressed in terms of σ, the temporal standard deviation of the water quality variable in the absence of trend. To estimate power of trend detection as a function of total change for a specific region, we can utilize the regional standard deviations shown earlier in Table 3-3.

For this analysis, let us choose one variable, ANC, and three regions to represent the anticipated range of temporal variability. NLS-1E represents low temporal variability, whereas NLS-1A and Eastern Streams represent medium and high variability, respectively. A cautionary note is in order. In each case, the tables represent average values for the "better" locations in the region in terms of data availability. There is no guarantee that these values are truly representative of regional behavior, and certainly individual lake variances would differ from these average values.

To reduce the number of cases to be considered, let us choose the arithmetic mean of the four seasonal (quarterly) temporal standard deviations of ANC for each region. These average standard deviations (in μeq L^{-1}) are 4.8 for NLS-1E (low variability), 27.2 for NLS-1A (medium variability) and 32.1 for Streams (high variability).

Under the assumption of linear trend, we can plot the total change occurring over time for a stated trend magnitude, T/σ, and temporal standard deviation, σ. We have included such plots below each of the power curves (Figures 4-1 through 4-4) using the three standard deviations described in Section 3. These plots are specific to the assumed temporal standard deviations and are included simply to illustrate how the power curves would be used in a given situation--not necessarily to suggest that these would be the actual powers anticipated for ANC in the given regions.

An example might help to interpret the figures. Suppose that we are interested in a trend magnitude of 0.2 standard deviations per year, equivalently 0.05 standard deviations per quarter occurring over a 10-year period. From Figure 4-3 on page 46, we see that the total change occurring (lower graph) in a medium variability system (NLS-1A, ANC standard deviation of 27.2 μeq L^{-1}) would be just over 50 μeq L^{-1}. A simple calculation verifies this.

$$(10 \text{ years})\ (0.2\ \sigma/\text{year})\ (27.2\ \mu\text{eq } L^{-1})/\sigma = 54.2\ \mu\text{eq } L^{-1}$$

From the upper graph we see that annual sampling (10 samples) would provide a power of about 0.35 under the hypothesized trend, whereas quarterly sampling (40 samples) would provide a power of about 0.95.

4.2 MULTIPLE LAKES

The primary monitoring objective discussed to this point has been detecting trends in individual lakes. It will often be desirable, however, to also consider trends in average conditions over several lakes.

Although there are many possible ways to define "average," it is reasonable at the network design stage to limit discussion to simple arithmetic averages (regional sample mean) over a group of lakes with one observation per time period per lake. The statistical objective of monitoring is then the detection of changes in the regional mean over time for specified water quality variables.

4.2.1 Statistical Characteristics of the Regional Mean

Actually this objective amounts to simply replacing the individual lake water quality variables considered thus far with new variables, which are regional means. Trends in the new variables would be detected in exactly the same way as trends in the individual lake variables. In order to determine the anticipated power of trend detection for regional means, however, we need to determine the temporal variance and correlation structure of the regional means. Although these characteristics could be determined from analysis of historical time series of regional means, general results may be obtained more easily by relating regional mean characteristics to those of individual lakes. Several simplifying assumptions are used in the following development.

First, the temporal variance of the regional mean, var ($\bar{x}$) is given by

$$\mathrm{var}\,(\bar{x}) = \mathrm{var}\,[\tfrac{1}{n}\,\Sigma\, x_{i,t}]$$

$$= (\tfrac{1}{n})^2\,[\sum_{i=1}^{n} \mathrm{var}\,(x_{i,t}) + 2\sum_{i<j}^{n} \mathrm{cov}\,(x_i,x_j)_t]$$

where n = number of lakes sampled
$x_{i,t}$ = deseasonalized or residual observation at lake i, time t (after removal of seasonal variation)

We assume that there is some regional temporal variance, σ^2, that may be used to replace the terms var ($x_{i,t}$) at this early, network design stage. We further assume that this variance is stationary. The spatial covariance terms may be written as

$$\mathrm{cov}\,(x_i,x_j)_t = \rho(x_i,x_j)\,\sqrt{(\sigma^2{}_i)(\sigma^2{}_j)}$$
$$= \rho_{ij}\sigma^2$$

where ρ_{ij} = the spatial correlation coefficient between stations i and j and
σ^2 = the regional temporal variance.

We can now write a simplified expression for the variance of the regional mean as follows.

$$\mathrm{var}\,(\bar{x}) = (\tfrac{1}{n})^2\,[n\sigma^2 + 2\sum_{i<j} \sigma^2\rho_{ij}]$$

$$\mathrm{var}\,(\bar{x}) = \frac{\sigma^2}{n}[1 + \bar{\rho}_o\,(n-1)]$$

where $\bar{\rho}_o$ = the average interstation correlation at lag zero
var ($\bar{x}$) = temporal variance of the regional mean

Now we have the temporal variance of the "new" variables, and all that remains is to find the temporal correlation structure.

We can write from the definition of temporal correlation,

$$\rho_{\bar{x}}(k) = \rho(\bar{X}_t, \bar{X}_{t+k}) = \frac{E[(\bar{X}_t - \mu_{\bar{x}_t})(\bar{X}_{t+k} - \mu_{\bar{x}_{t+k}})]}{\sqrt{(\sigma^2_{\bar{x}_t})\,\sigma^2_{\bar{x}_{t+k}}}}$$

After removal of season means, all μ's = 0. From stationarity assumptions, both variances in the denominator are equal to var($\bar{x}$), given above. Therefore,

$$\rho_{\bar{x}}(k) = \frac{\mathrm{cov}\,[\bar{X}_t, \bar{X}_{t+k}]}{\mathrm{var}\,(\bar{X})}$$

$$= \frac{E[(\bar{X}_t)(\bar{X}_{t+k})]}{\mathrm{var}\,(\bar{X})}$$

Expanding in terms of individual lake observations we obtain the following:

$$\rho_{\bar{x}}(k) = \frac{1}{n^2}\begin{bmatrix} \rho_{11}(k) + \rho_{12}(k) + \rho_{13}(k) + \ldots + \rho_{1n}(k) + \\ \rho_{21}(k) + \rho_{22}(k) + \ldots \\ \cdot \\ \cdot \\ \cdot \\ \rho_{n1}(k) + \ldots \qquad\qquad + \rho_{nn}(k) \end{bmatrix}$$

The entire term in brackets is a sum. The diagonal terms are lag-k autocorrelations at each station (lake) 1,...,n. The off-diagonal terms are lag-k cross correlations between stations. Each station pair appears twice. Assuming that the cross correlation terms are small (negligible) compared to the autocorrelation terms, we obtain

$$\rho_{\bar{x}}(k) = \frac{1}{n}(\bar{\rho}_k)$$

where $\bar{\rho}_k$ = the average of the n lag-k autocorrelations over all stations.

In particular for lag-one,

$$\rho_{\bar{x}}(1) = \frac{1}{n}\bar{\rho}_n$$

The lag-one autocorrelation coefficient of the regional mean is 1/n times the regional average lag-one value. Since the term $\bar{\rho}_1$ would typically be small for quarterly or less frequent sampling, the value of $\rho_{\bar{x}}(1)$ would generally be negligible. Thus temporal correlation will be ignored in the remainder of this section. Spatial correlation will be considered through its effect on var ($\bar{X}$) as developed above.

4.2.2 Detectable Changes in Regional Means

The same approach used earlier for determining the power of detecting a linear trend may now be applied to regional means. The individual lake temporal variance σ^2 is now replaced by var ($\bar{X}$). Everything else remains the same. Figures 4-5 through 4-8 present the detectable change as a function of the number of observations for given numbers of stations (lakes). The figures show two levels of average inter-lake (spatial) correlation, $\bar{\rho}_o$ = 0.2 and 0.4 and powers (1-β) of 0.90, 0.80, and 0.60. The case of $\bar{\rho}_o$ = 0.4 is considered only for 1-β = 0.20. In all cases, the significance level is constant at 0.10, and a linear trend (constant slope) occurs over the entire period of monitoring.

In general, as the number of stations, n, increases, the var ($\bar{X}$) decreases and the power increases. However, as the spatial correlation increases, the var ($\bar{X}$) also increases and power is reduced.

The curves are generalized by presentation of the detectable change (vertical axis) in standard deviations. The curves are independent of any time scale; thus they may be used for quarterly, semi-annual, or annual sampling. However, the observations are assumed to be temporally independent and equally spaced in time. The change indicated on the vertical axis is assumed to occur as a linear trend over the number of observations indicated on the horizontal axis. Application to a specific situation is best explained by example.

Suppose that in a given region, the average temporal standard deviation of sulfate concentration in individual lakes is 10 μeq L^{-1}. We can determine the detectable change with stated power for various time periods and numbers of lakes as follows. Consider the case of σ = 0.10 and ρ = 0.20 (Figures 4-6 and 4-7). Also consider annual sampling. Over a period of 10 years (10 observations in each lake), the detectable change in sulfate concentration for one lake would be three standard deviations (curve a, Figure 4-6), or 30 μeq L^{-1}. The trend magnitude or slope over that time would be 3.0 μeq L^{-1}/year. For four lakes with no spatial correlation, the detectable change in 10 years would be 1.5 standard deviations (as in curve b, Figure 4-6), or 15 μeq L^{-1}. The trend slope would be 1.5 μeq L^{-1}/year. For 16 lakes, the detectable change would be 7.5 μeq L^{-1} (as in curve c, Figure 4-6), with a trend slope of 0.75 μeq L^{-1}/year.

If spatial correlation exists, however, the detectable change is larger. For example, with 16 lakes and $\bar{\rho}_o$ = 0.4, curve e of Figure 4-7 applies, and the detectable change over 10 years of annual sampling is 2.0 standard deviations or 20 μeq L^{-1}, a trend slope of 2.0 μeq L^{-1}/year.

Figure 4-7 indicates that when the average inter-lake correlation is 0.4, the advantage of increasing the number of lakes from four (curve d) to 16 (curve e) is slight. In the real world, this effect would be even more pronounced, since the average inter-lake correlation would increase as the number of lakes sampled within a region increased. Thus, the reduction in detectable change would actually be less than that shown in the figures. Obviously, inter-lake correlation has a significant impact on the power of detecting trends in regional means.

An important concern, therefore, is how large we might expect inter-lake correlations to be. Given the paucity of data records for multiple lakes in a given region over long times, this is a difficult question to address. For a single example, though, we computed inter-lake correlations for 11 lakes (those with most complete data records) in NLS subregion 1A. The values for all possible pairings of lakes are shown in Tables 4-1 and 4-2 for ANC and sulfate, respectively.

Each value is based on 40 monthly observations with a few missing values. For ANC, estimated inter-lake correlations range from -0.090 to +0.841 with an average of +0.358. For sulfate the range is -0.232 to +0.724 with an average of +0.252. As indicated by the map of sampling locations in Newell (1987), however, many of the lakes are very close together. We therefore

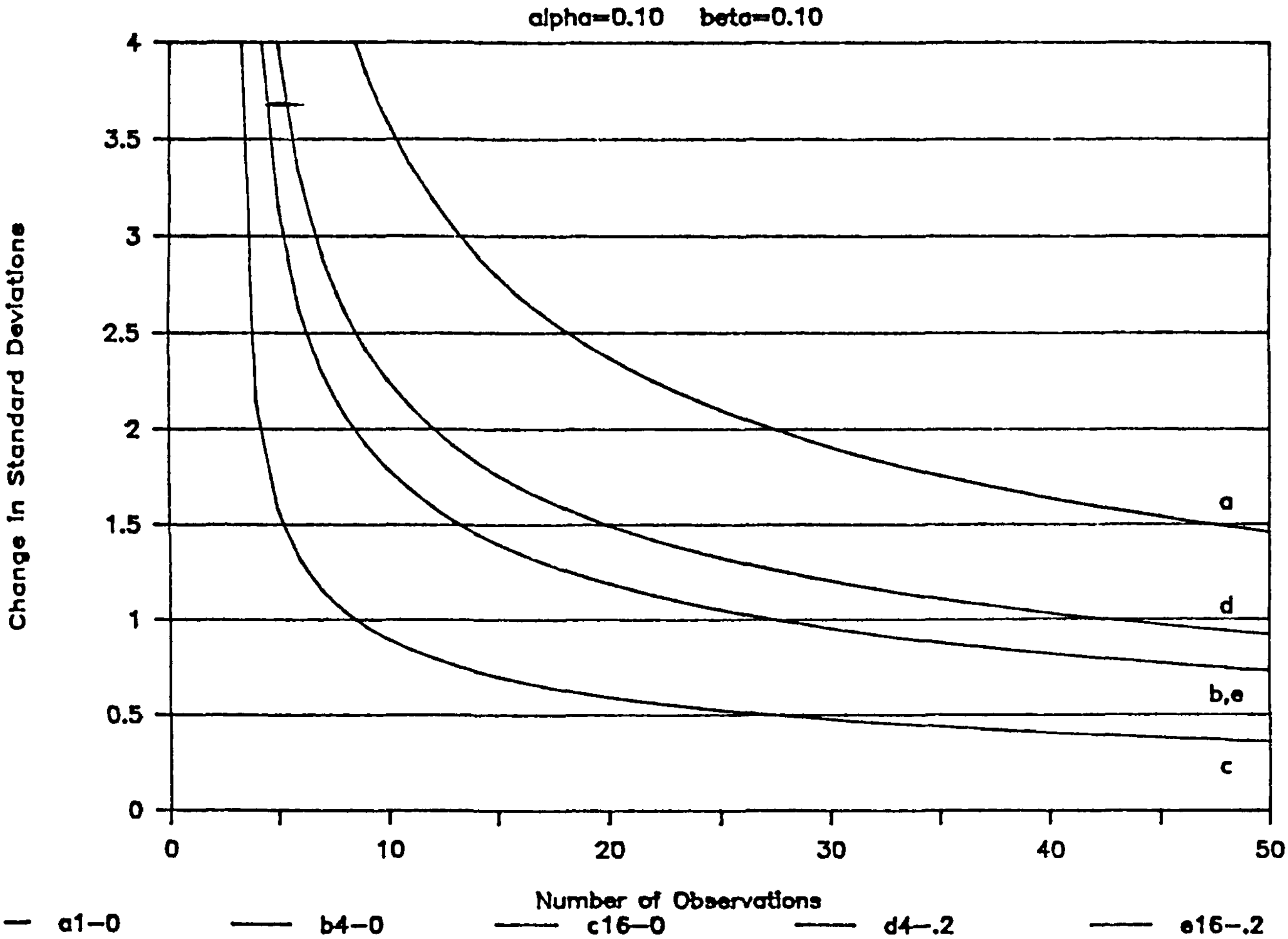


Figure 4-5. Level of detectable trend for α=0.10 and β=0.10 for five configurations of number of lakes and spatial correlation = 0.0 and 0.2.

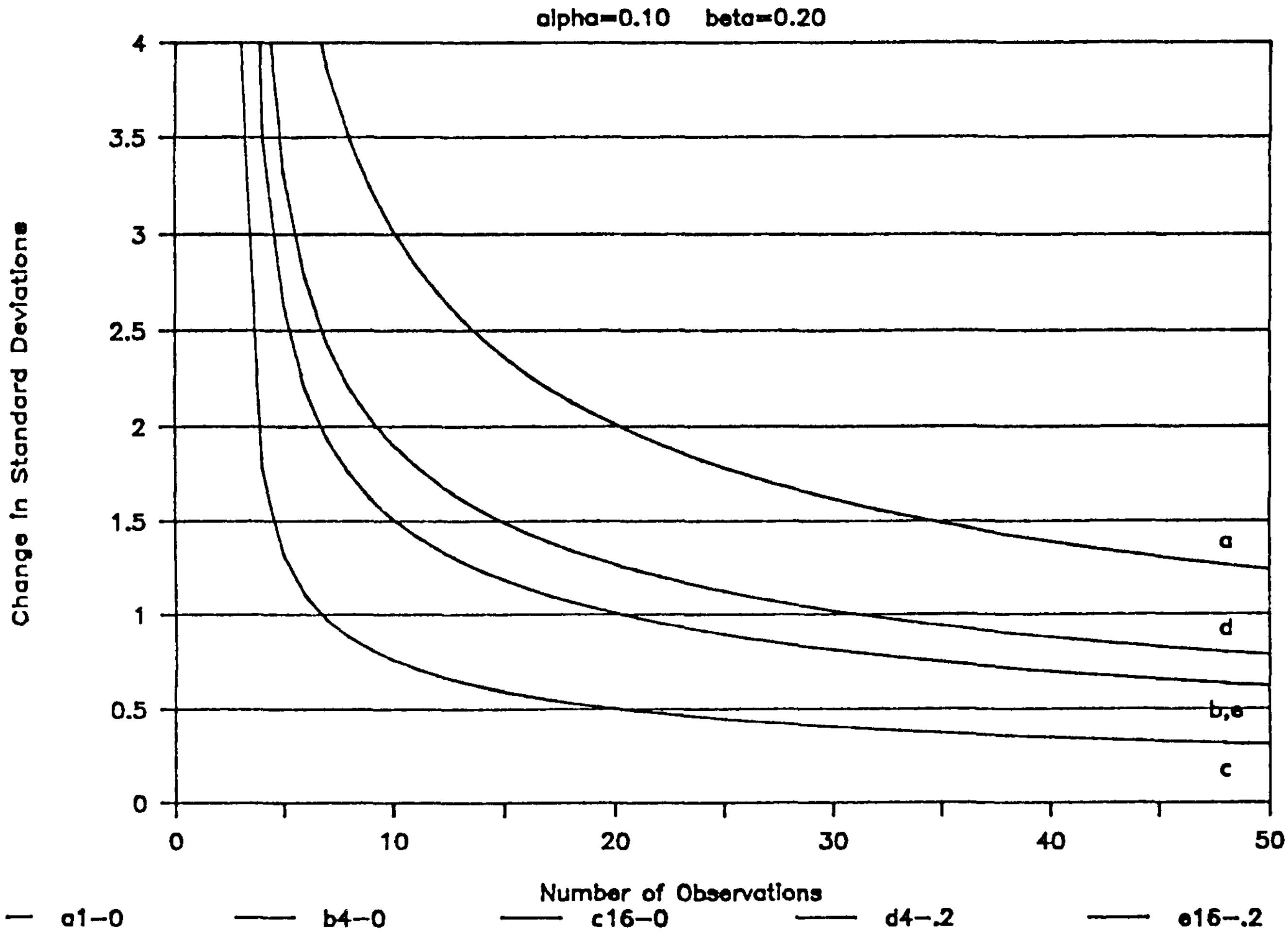


Figure 4-6. Level of detectable trend for α=0.10 and β=0.20 for five configurations of number of lakes and spatial correlation = 0.0 and 0.2.

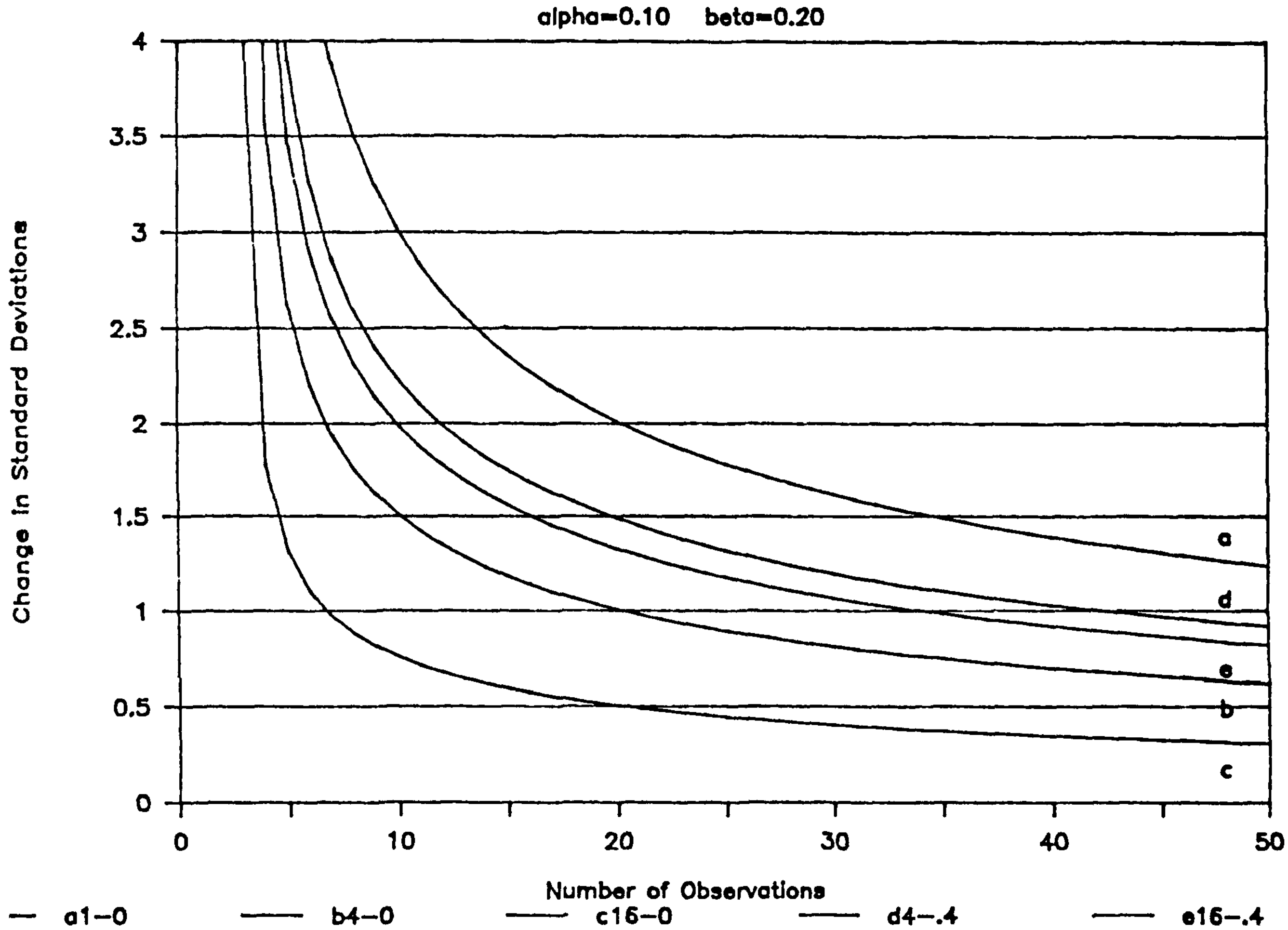


Figure 4-7. Level of detectable trend for $\alpha=0.10$ and $\beta=0.20$ for five configurations of number of lakes and spatial correlation = 0.0 and 0.4.

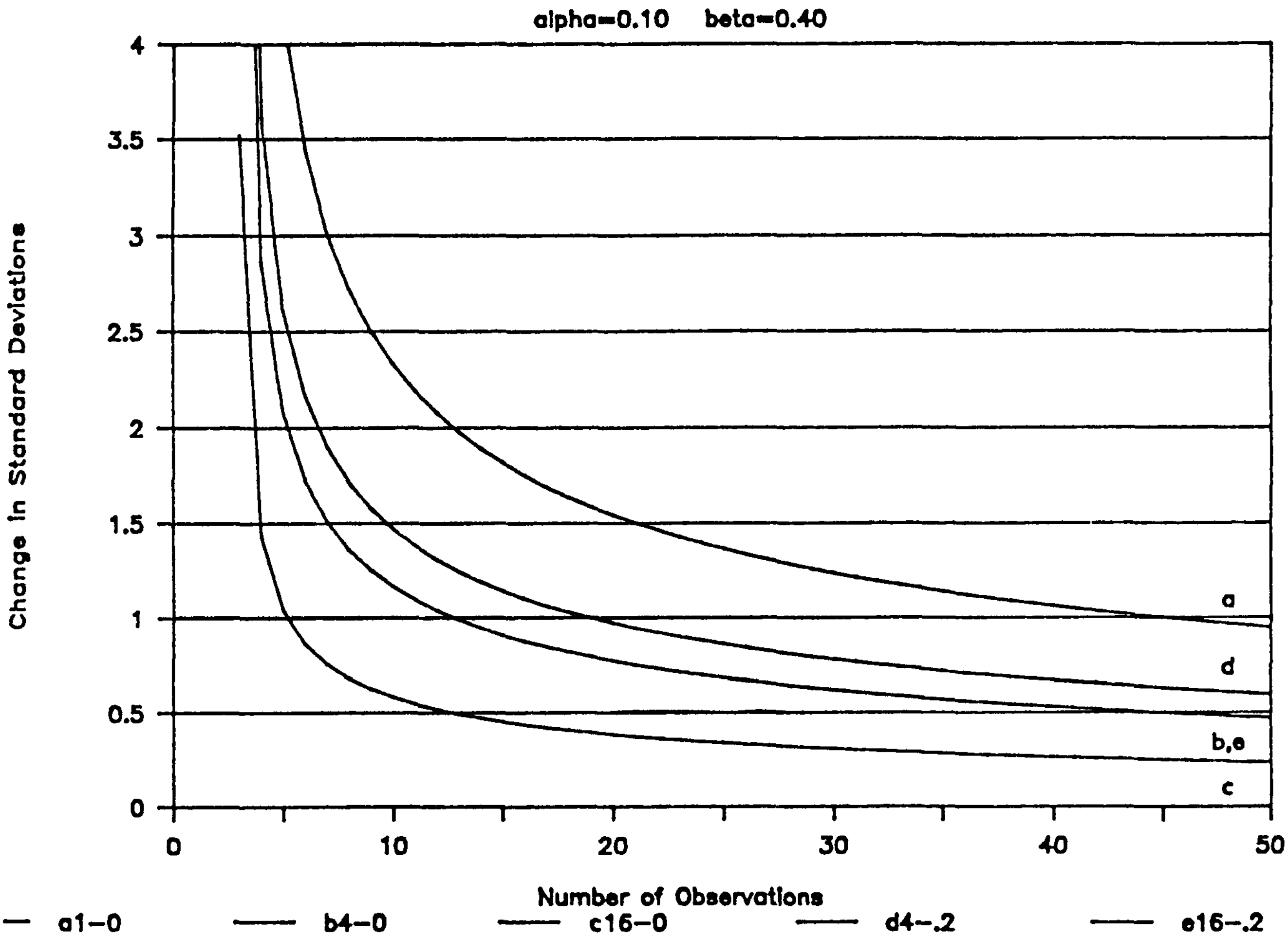


Figure 4-8. Level of detectable trend for α=0.10 and β=0.40 for five configurations of number of lakes and spatial correlation = 0.0 and 0.2.

TABLE 4-1. BETWEEN-LAKE CORRELATIONS FROM MONTHLY DATA FOR ANC ($\approx$ 40 MONTHS OF DATA) FOR 11 LAKES IN NLS SUBREGION 1A

Between Lake	and Lake	Correlation	Between Lake	and Lake	Correlation
1	2	0.190	4	5	0.319
1	3	0.311	4	6	0.488
1	4	0.121	4	7	0.037
1	5	0.485	4	8	0.325
1	6	0.446	4	9	0.696
1	7	0.094	4	10	0.367
1	8	0.331	4	11	0.546
1	9	0.236	5	6	0.468
1	10	0.254	5	7	0.249
1	11	0.205	5	8	0.588
2	3	0.381	5	9	0.481
2	4	0.841	5	10	0.334
2	5	0.383	5	11	0.503
2	6	0.519	6	7	0.419
2	7	0.038	6	8	0.559
2	8	0.451	6	9	0.577
2	9	0.738	6	10	0.355
2	10	0.372	6	11	0.528
2	11	0.505	7	8	0.024
3	4	0.276	7	9	-0.018
3	5	0.507	7	10	0.228
3	6	0.195	7	11	0.238
3	7	-0.090	8	9	0.611
3	8	0.376	8	10	0.284
3	9	0.251	8	11	0.477
3	10	0.114	9	10	0.525
3	11	0.393	9	11	0.467
Average correlation = 0.358			10	11	0.118

Lake designation, from Newell et al. (1987)	Lake number used in Tables 4-1 and 4-2
1A1-071	1
1A1-105	2
1A2-077	3
1A1-087	4
1A1-102	5
1A1-106	6
1A1-107	7
1A1-109	8
1A1-110	9
1A1-113	10
1A1-078	11

TABLE 4-2. BETWEEN-LAKE CORRELATIONS FROM MONTHLY DATA FOR SULFATE (≈ 40 MONTHS OF DATA) FOR 11 LAKES IN NLS SUBREGION 1A

Between Lake	and Lake	Correlation	Between Lake	and Lake	Correlation
1	2	0.011	4	5	0.561
1	3	0.256	4	6	0.344
1	4	0.059	4	7	-0.144
1	5	0.466	4	8	0.461
1	6	0.470	4	9	0.275
1	7	-0.156	4	10	0.166
1	8	0.224	4	11	0.143
1	9	0.161	5	6	0.538
1	10	0.366	5	7	-0.226
1	11	0.288	5	8	0.364
2	3	0.542	5	9	0.036
2	4	0.609	5	10	-0.008
2	5	0.463	5	11	0.467
2	6	0.256	6	7	-0.114
2	7	0.085	6	8	0.464
2	8	0.415	6	9	0.442
2	9	0.246	6	10	0.249
2	10	0.059	6	11	0.466
2	11	0.145	7	8	-0.103
3	4	0.474	7	9	0.100
3	5	0.156	7	10	0.011
3	6	0.438	7	11	-0.232
3	7	0.065	8	9	0.724
3	8	0.325	8	10	0.250
3	9	0.410	8	11	0.459
3	10	0.512	9	10	0.334
3	11	0.004	9	11	0.311
			10	11	0.192

Average correlation = 0.252

regard these results as atypical and "on the high side," both in terms of maximum inter-lake correlations and average inter-lake correlations for a region. In the example, no attempt was made to relate inter-lake correlations to distance between lakes, although this would be a logical next step in the analysis of a particular region (Hirsch and Gilroy, 1985). We present this example, however, only to suggest that our choices of $\bar{\rho}_0$ = 0.0, 0.20, and 0.40 (in Figures 4-5, 4-6, and 4-7) have some relevance to a real world situation.

4.3 CASE STUDIES, INDIVIDUAL LAKES

4.3.1 Clearwater Lake, Ontario

In order to illustrate the application of statistical tests for trend, and to compare the performance of alternative methods, we applied the tests to historical data from Clearwater Lake, Ontario (Nicholls, 1987). The variables studied were ANC, sulfate, sulfate/ANC, and sulfate/(calcium+magnesium). All samples were depth-integrated composites. The statistical trend tests studied were Seasonal Kendall (SK), with and without correction for serial correlation, and analysis of covariance (ANOCOV) on both raw data and ranks of data.

The Clearwater Lake data were used for the case study for two reasons. A long record is available, and significant trends of increasing ANC and decreasing sulfate are known to exist. Unfortunately, perhaps, the trend magnitudes are so large that all statistical tests indicate significant trends in approximately the minimum time required to obtain stable values of the test statistics. Thus little difference in performance between tests is apparent.

The case study assumes quarterly sampling. Since Clearwater Lake was sampled more frequently, quarterly values were obtained by subsampling, that is, choosing the value that appears closest to the center of the quarter. Quarters were defined as (1) December, January, February, (2) March, April, May, etc.

4.3.1.1 Sulfate Concentration--

Figure 4-9 is a plot of quarterly sulfate observations beginning in summer of 1973. Figure 4-10 is the corresponding correlogram. No seasonal pattern is apparent, and the strong autocorrelation is removed by detrending, using ordinary least squares (correlogram of Figure 4-11). The detrended data have a skewness coefficient of -0.882, which is significant at the 1% level. The trend magnitude, from Ordinary Least Squares (OLS), is 0.221 mg L^{-1}/quarter or 0.161 standard deviations per quarter. Figure 4-12 portrays the results of applying ANOCOV to both raw sulfate data and ranks in successive trials at a nominal significance level of 5%. Each trial begins at the start of the historical record and ends with the quarter shown on the horizontal axis. Missing values are not included in the number of quarters. The number of quarters used ranges from 9 to 44. The value of the test statistic is shown on the vertical axis, and the critical values are indicated with diamonds. For both the original data and ranks, ANOCOV indicates a significant trend after 16 observations.

Figure 4-13 presents the results of applying the SK test, both with and without the serial correlation correction, to the same data. The rejection value of the test statistic is 1.96 for a nominal significance level of 5%. The SK tests indicate significant trend after 14 (with correction) and 13 (without correction) observations. For longer records, the value of the SK test statistic is much larger (more negative) when the serial correlation correction is not used. Since the detrended data are not correlated, the uncorrected test is preferred.

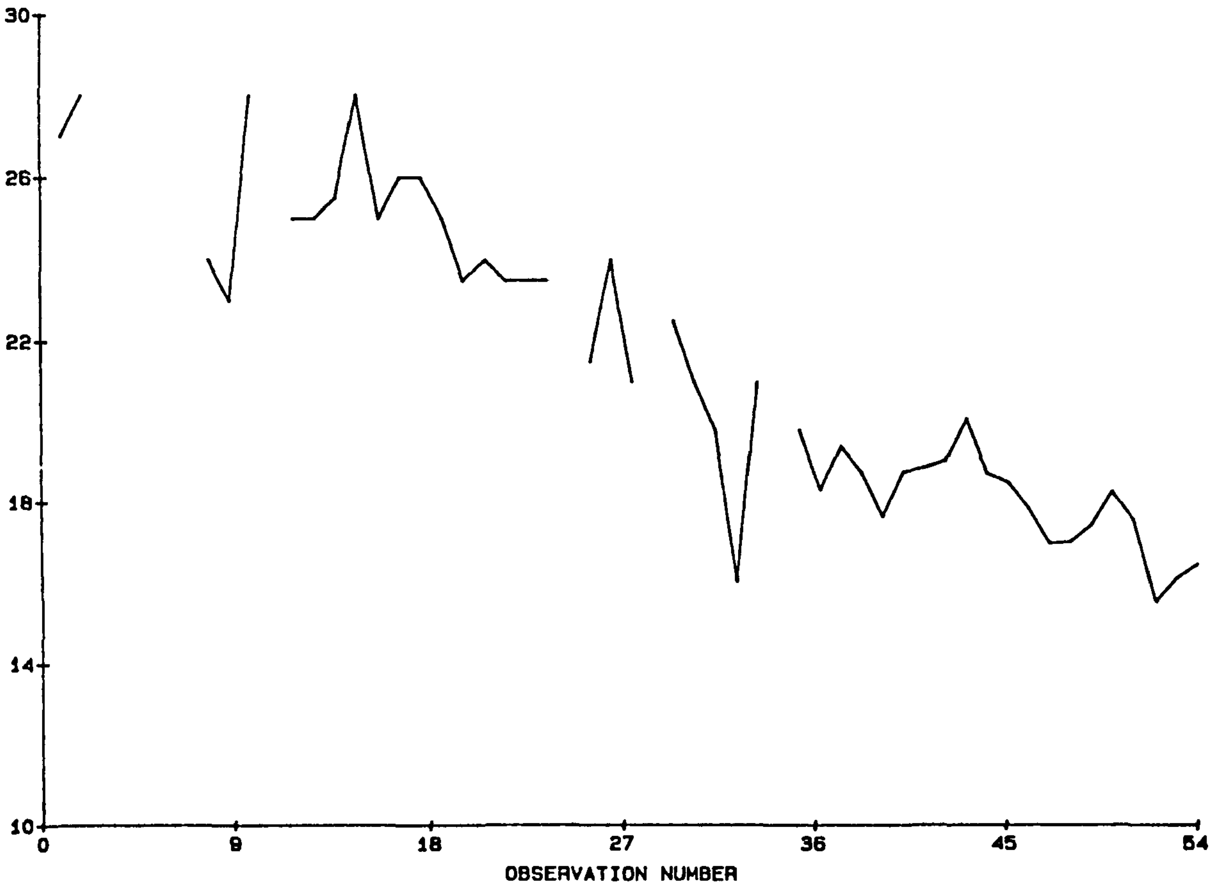


Figure 4-9. Quarterly sulfate observations beginning in summer of 1973.

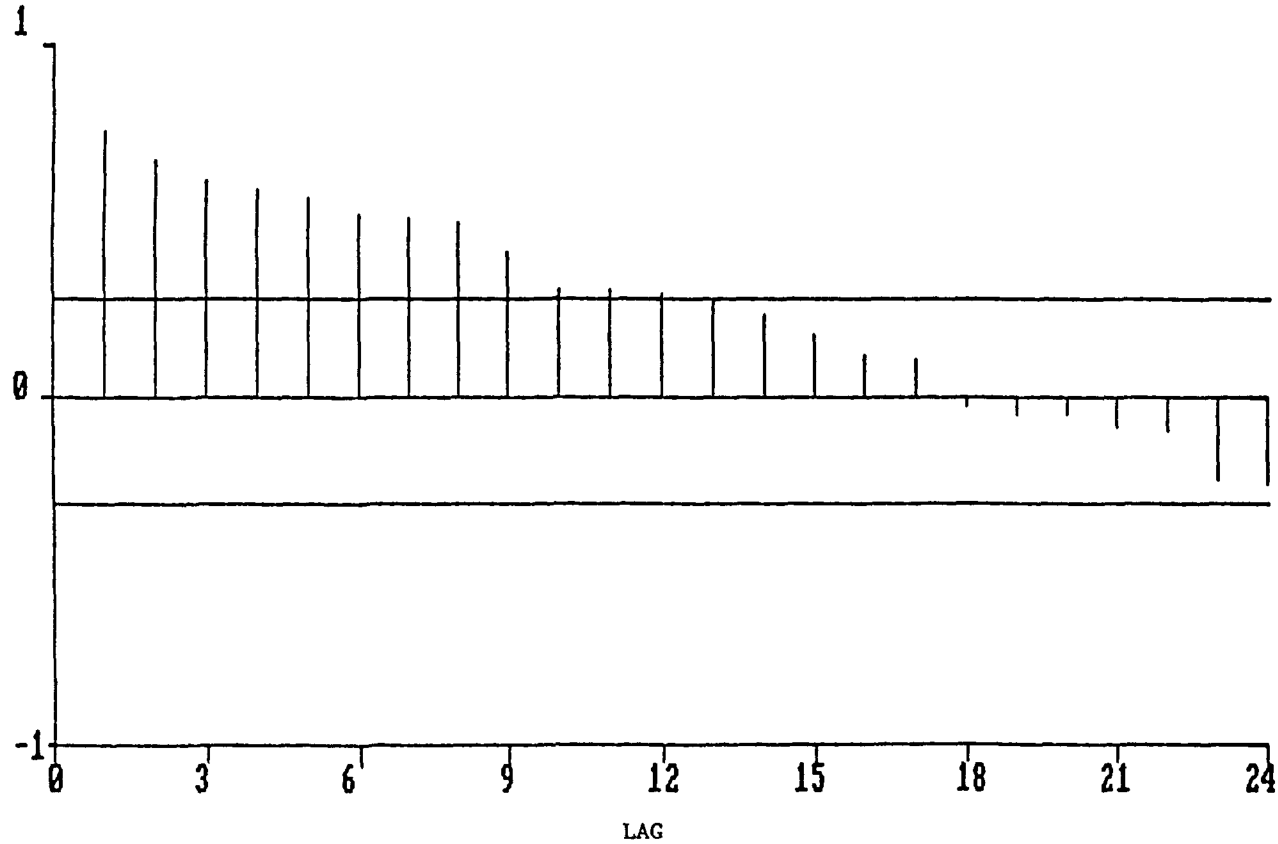


Figure 4-10. Correlogram of quarterly sulfate data shown in Figure 4-9.

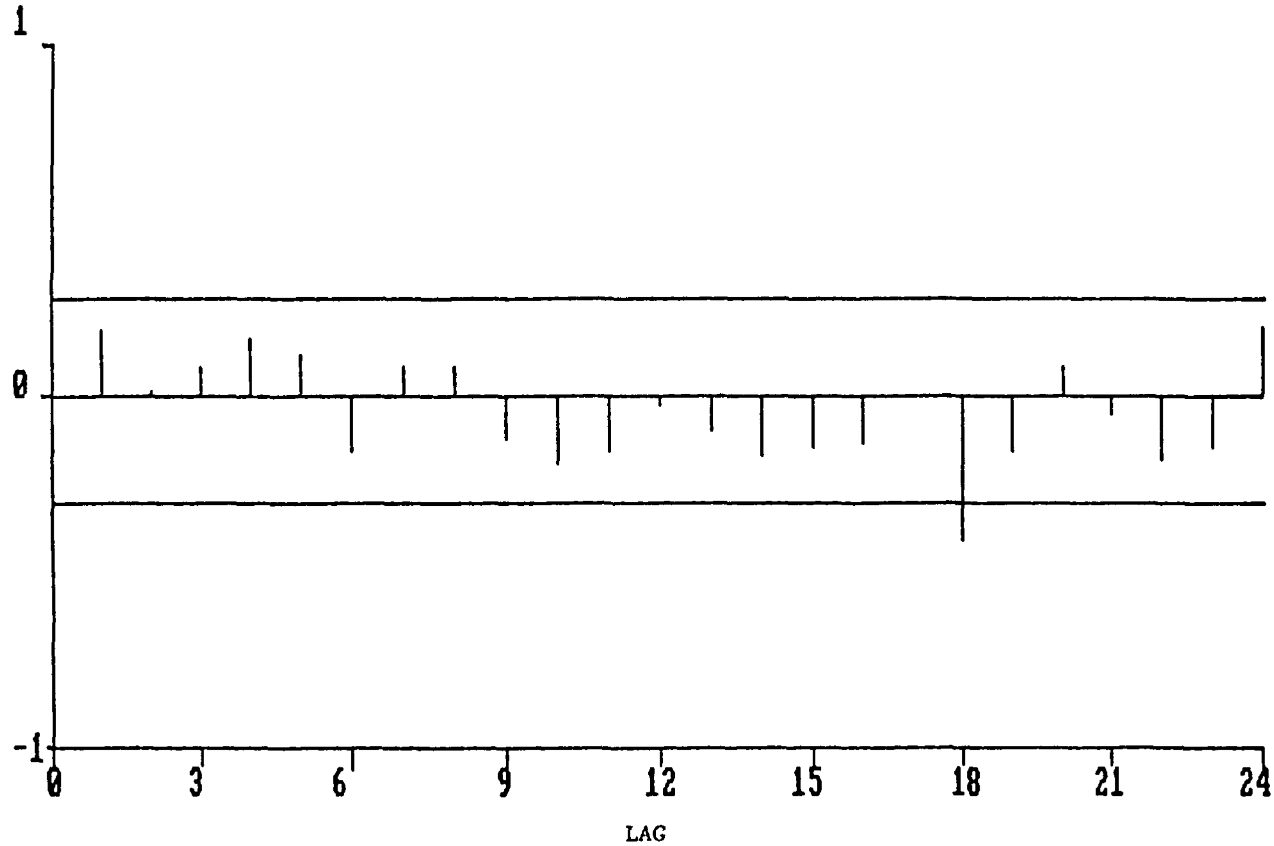


Figure 4-11. Correlogram of quarterly sulfate data shown in Figure 4-9 after detrending with ordinary least squares.

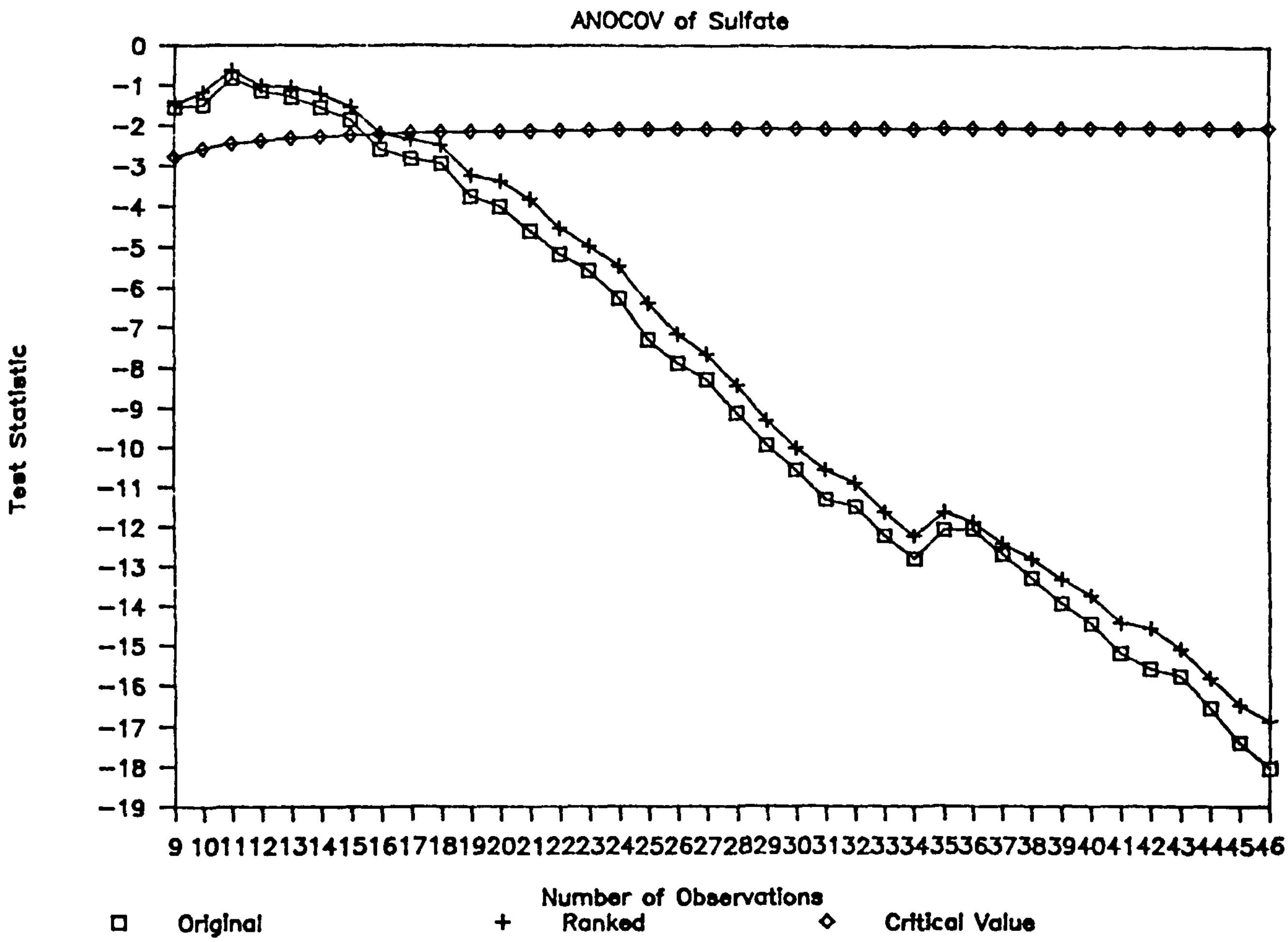


Figure 4-12. Results of ANOCOV on raw sulfate data and on ranks of sulfate data. Critical value of the test statistic is shown for each number of observations. The test is significant when the calculated statistic is more negative than the critical value.

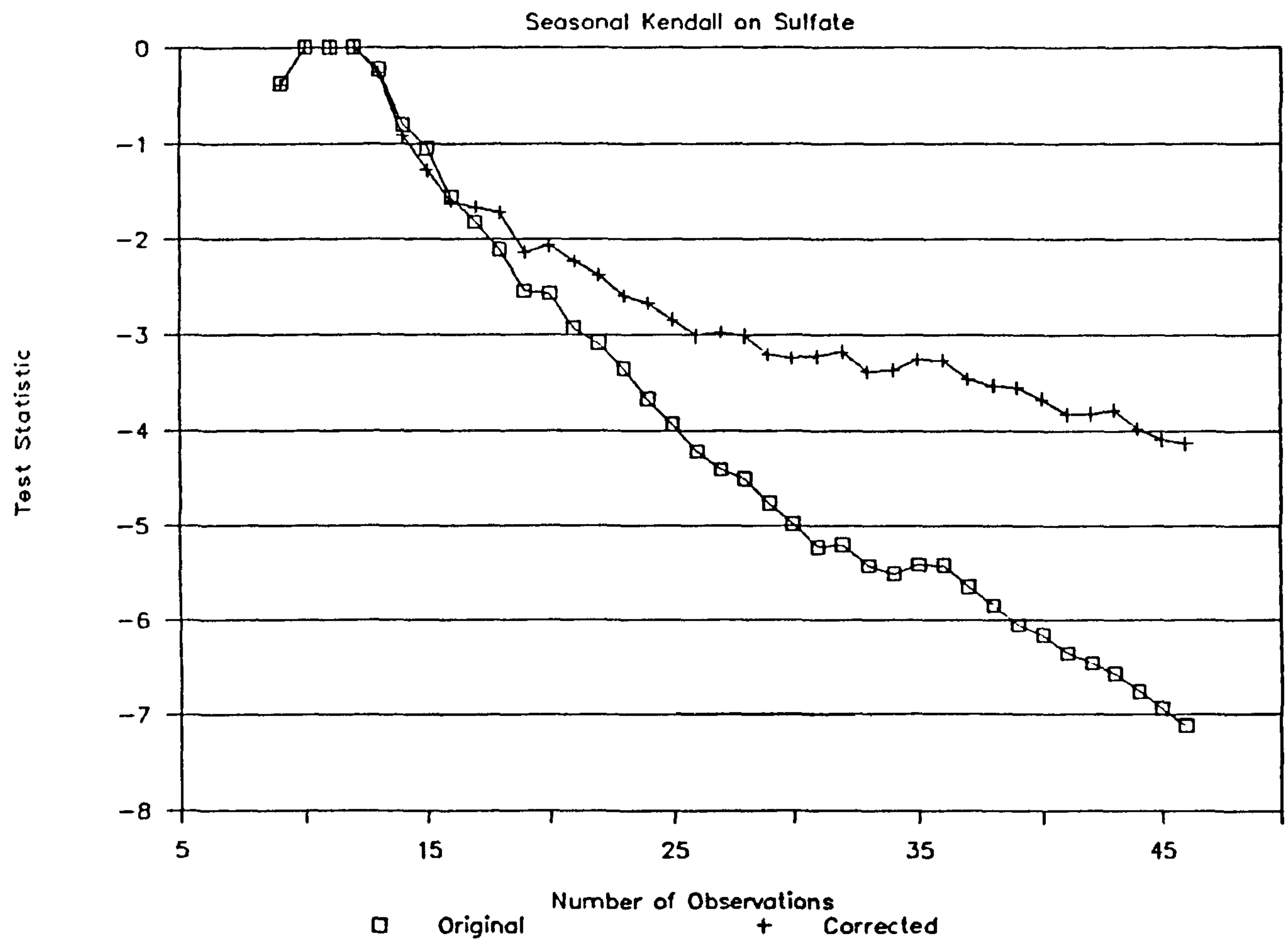


Figure 4-13. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw sulfate data.

4.3.1.2 Acid Neutralizing Capacity--

Raw ANC data, beginning with fall of 1980, are plotted in Figure 4-14 and the correlogram is presented in Figure 4-15. Lags one, three, and four show significant autocorrelation. This correlation is removed upon detrending by OLS (Figure 4-16). No significant seasonality is apparent. The detrended data do not show significant skewness at the 5% level. The OLS trend magnitude over the period of record is 0.0348 mg L^{-1} as calcium carbonate per quarter or 0.170 standard deviations per quarter.

Results of ANOCOV are shown in Figure 4-17. The original data show a significant trend after 11 observations, while the ranks show a significant trend after 16 observations. The test statistic is extremely variable over the first four years of data for both tests. The SK test statistics (Figure 4-18) are also quite variable over the first four years. The test without correlation correction consistently shows a significant trend after 15 quarters. The corrected test shows trend consistently after 16 quarters.

4.3.1.3 Sulfate/ANC--

The sulfate/ANC ratios beginning with fall of 1973 are plotted in Figure 4-19, and the correlogram is presented in Figure 4-20. Only lag-one correlation appears significant, and detrending results in significant lag-two correlation (Figure 4-21). Seasonality does not appear to be significant. The detrended data are not significantly skewed at the 5% level. The OLS trend magnitude over the period of record is 0.190 mg L^{-1}/quarter or 0.102 standard deviations per quarter.

The ANOCOV test statistics (Figure 4-22) are again highly variable for the first 14 observations. ANOCOV on ranks shows trend consistently after 14 observations, whereas ANOCOV on raw data shows trend consistently after 17 observations. The SK test shows significant trend consistently after 15 observations, without correction, and after 16 observations with correction for serial correlation (Figure 4-23).

4.3.1.4 Sulfate/(Calcium + Magnesium)--

The sulfate/(calcium + magnesium) ratio (Figure 4-24, beginning with summer of 1973) shows significant autocorrelation (Figure 4-25), which is removed by detrending (Figure 4-26). The data are not significantly skewed. Trend magnitude from OLS is 0.0239 or 0.102 mg L^{-1} per quarter.

ANOCOV finds significant trend after 21 observations for both raw data and ranks (Figure 4-27). The SK test (Figure 4-28), finds significant trend after 22 or 23 observations for the uncorrected and corrected versions, respectively.

4.3.1.5 Summary of Trend Testing Results--

The example data are generally characterized by symmetric distributions, little apparent seasonality, and little or no significant serial correlation. Trend magnitudes in the Clearwater Lake data are quite large, ranging from 0.10 to 0.17 standard deviations per quarter. Consequently, all four tests are able to detect trends quickly. Trends in sulfate, ANC, and sulfate/ANC are detected by all tests in 13 to 16 observations. The sulfate/(calcium + magnesium) ratio requires 21 to 23 observations.

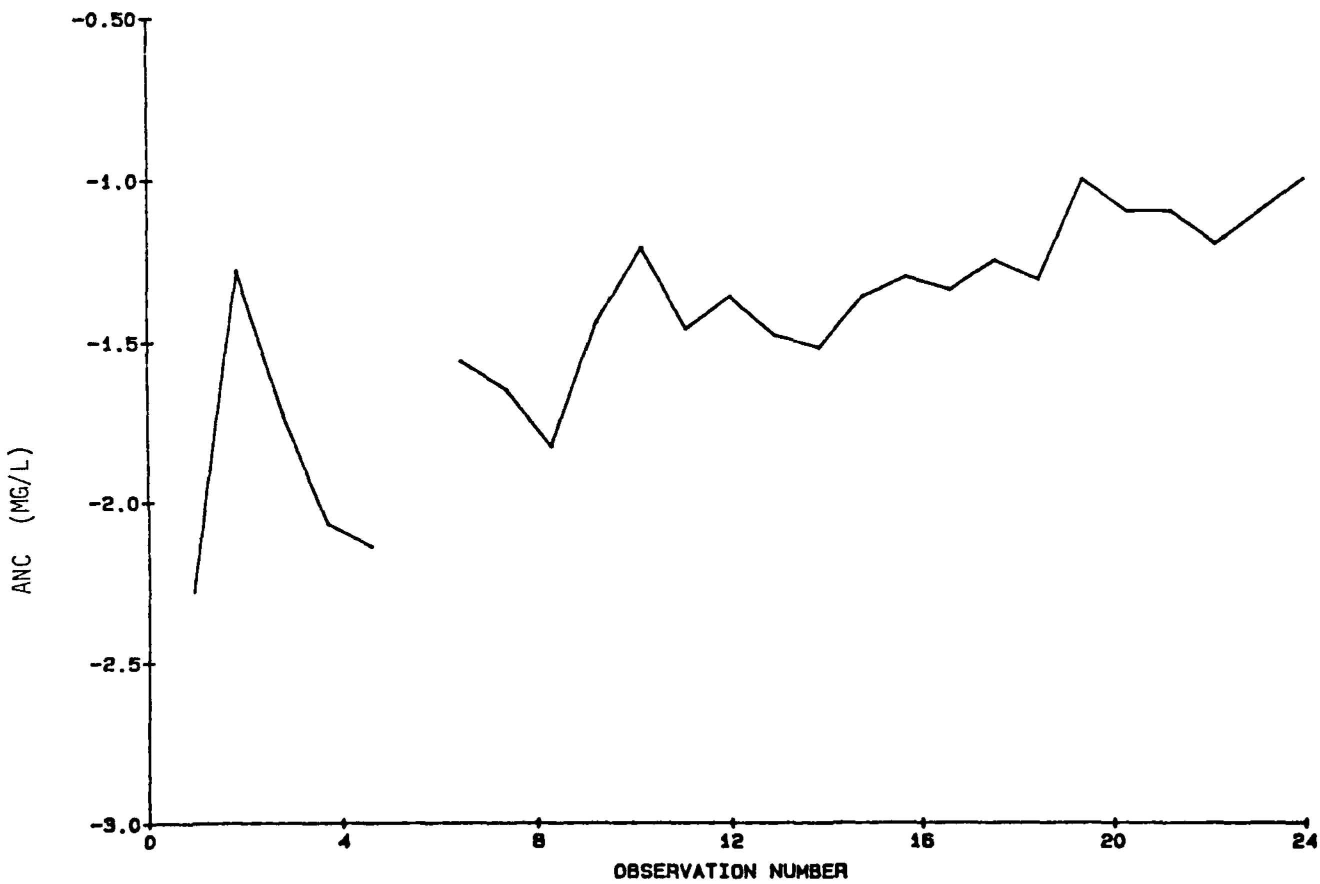


Figure 4-14. Quarterly ANC observations, mg L^{-1} as calcium carbonate, for Clearwater Lake, Ontario, beginning fall of 1980.

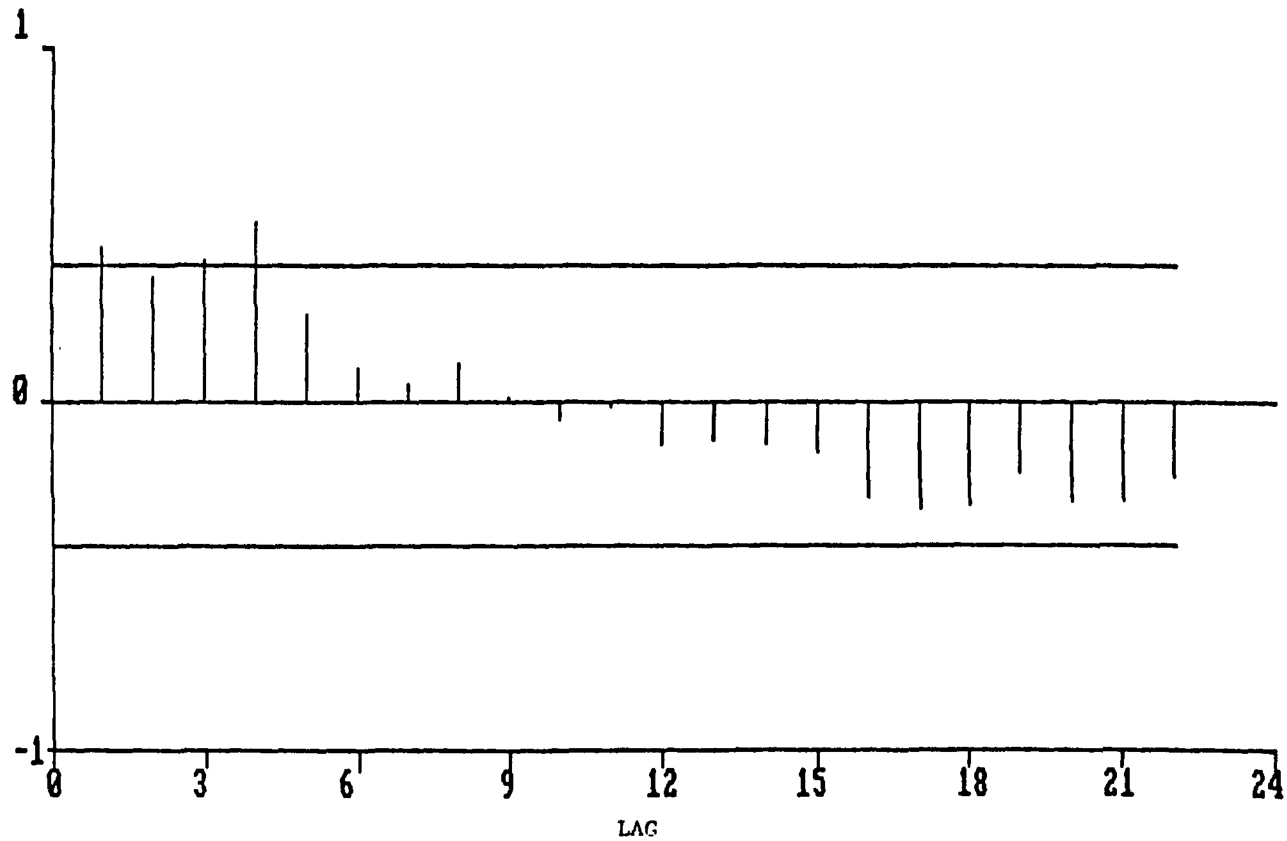


Figure 4-15. Correlogram of raw ANC data in Figure 4-14.

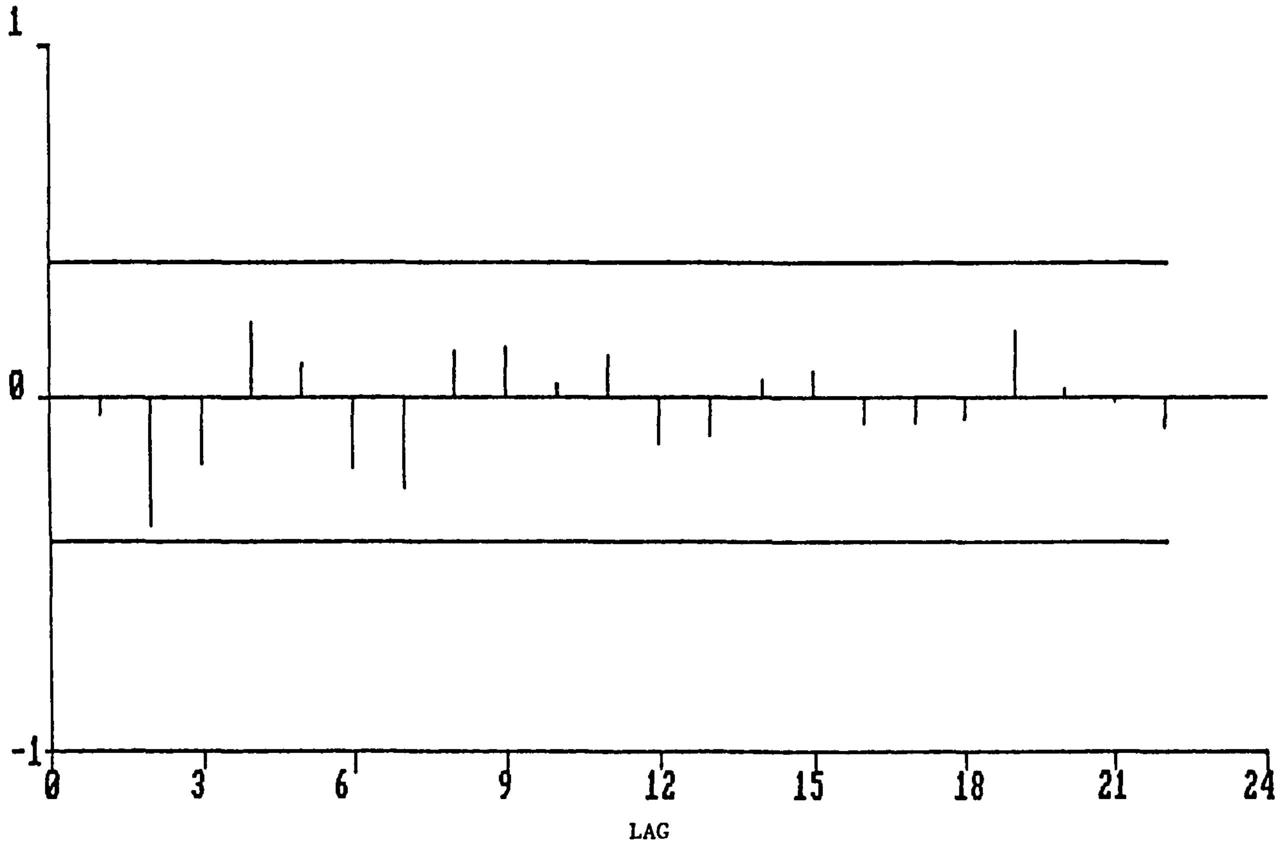


Figure 4-16. Correlogram of ANC data shown in Figure 4-14 after detrending by ordinary least squares.

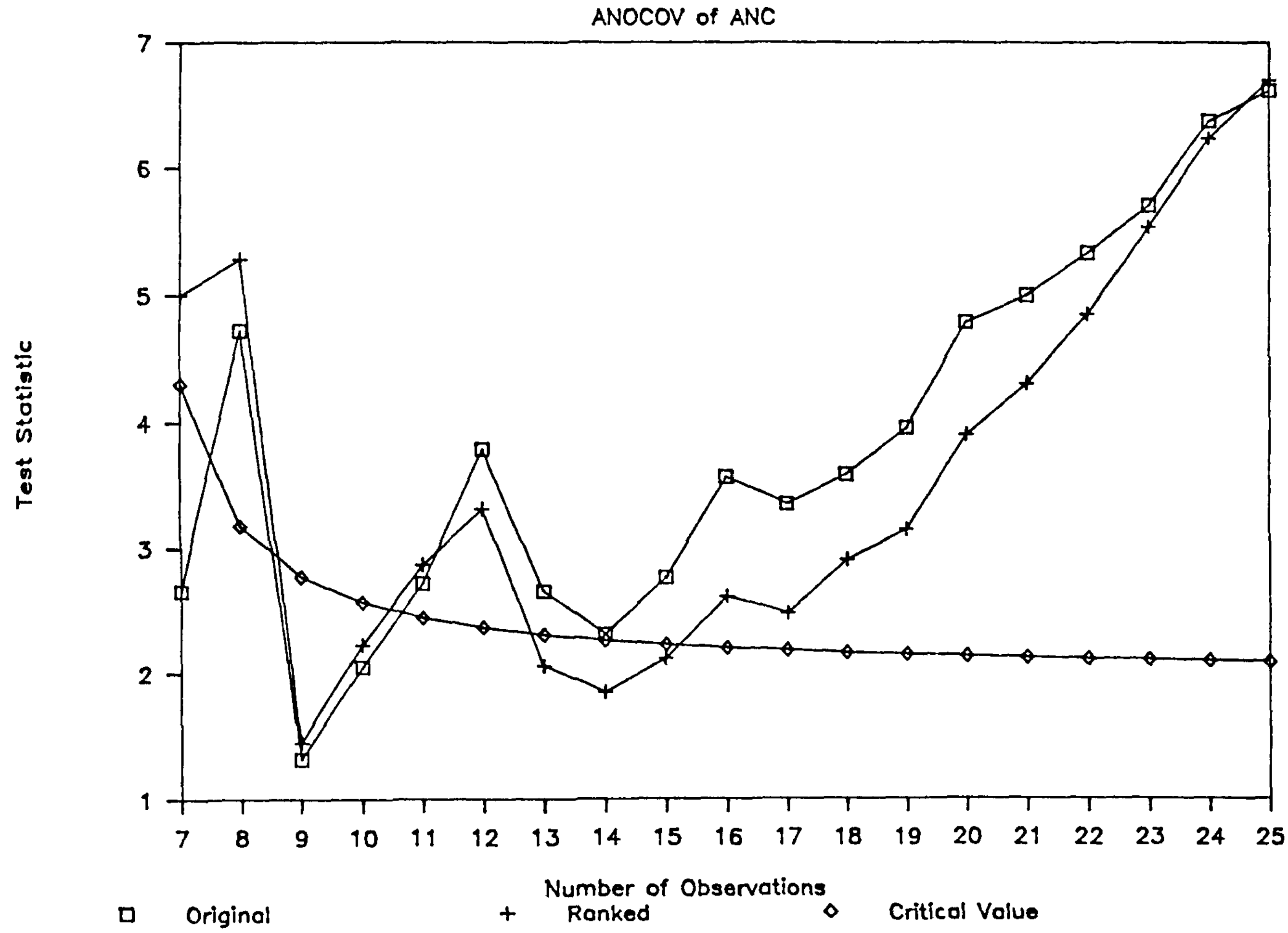


Figure 4-17. Results of ANOCOV on raw ANC data and on ranks of ANC data. Critical value of the test statistic is shown for each number of observations. The test is significant when the calculated statistic is larger than the critical value.

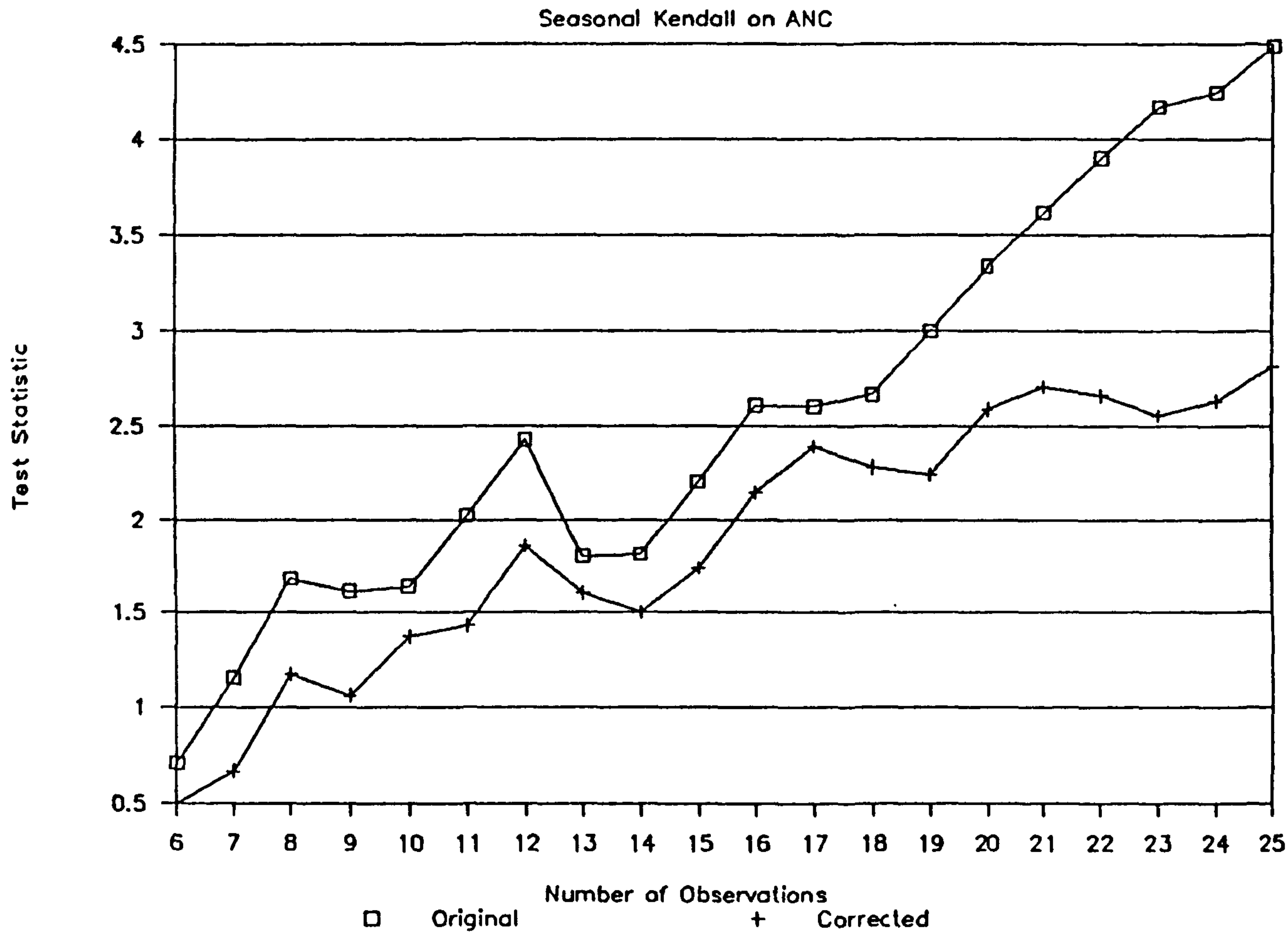


Figure 4-18. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw ANC data.

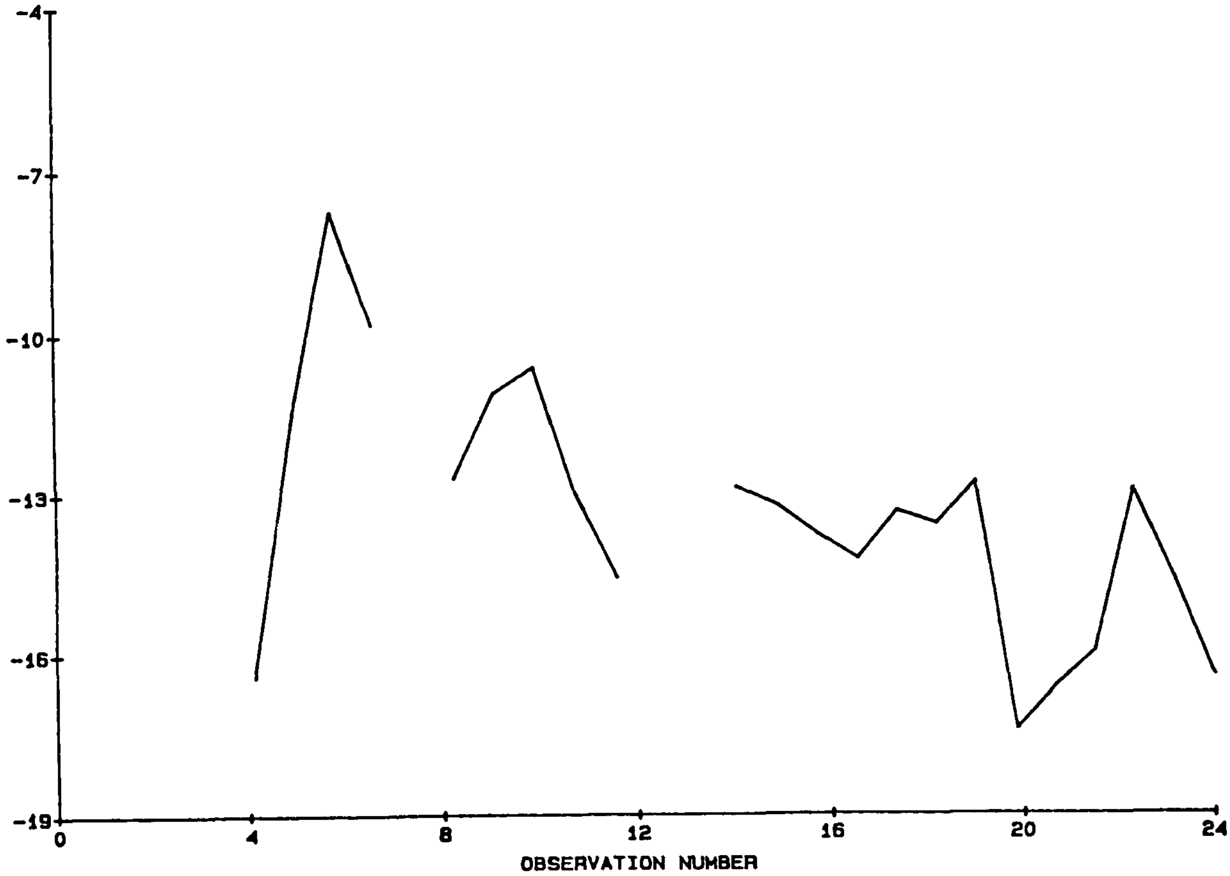


Figure 4-19. Quarterly sulfate/ANC ratios for Clearwater Lake, Ontario, beginning fall of 1980.

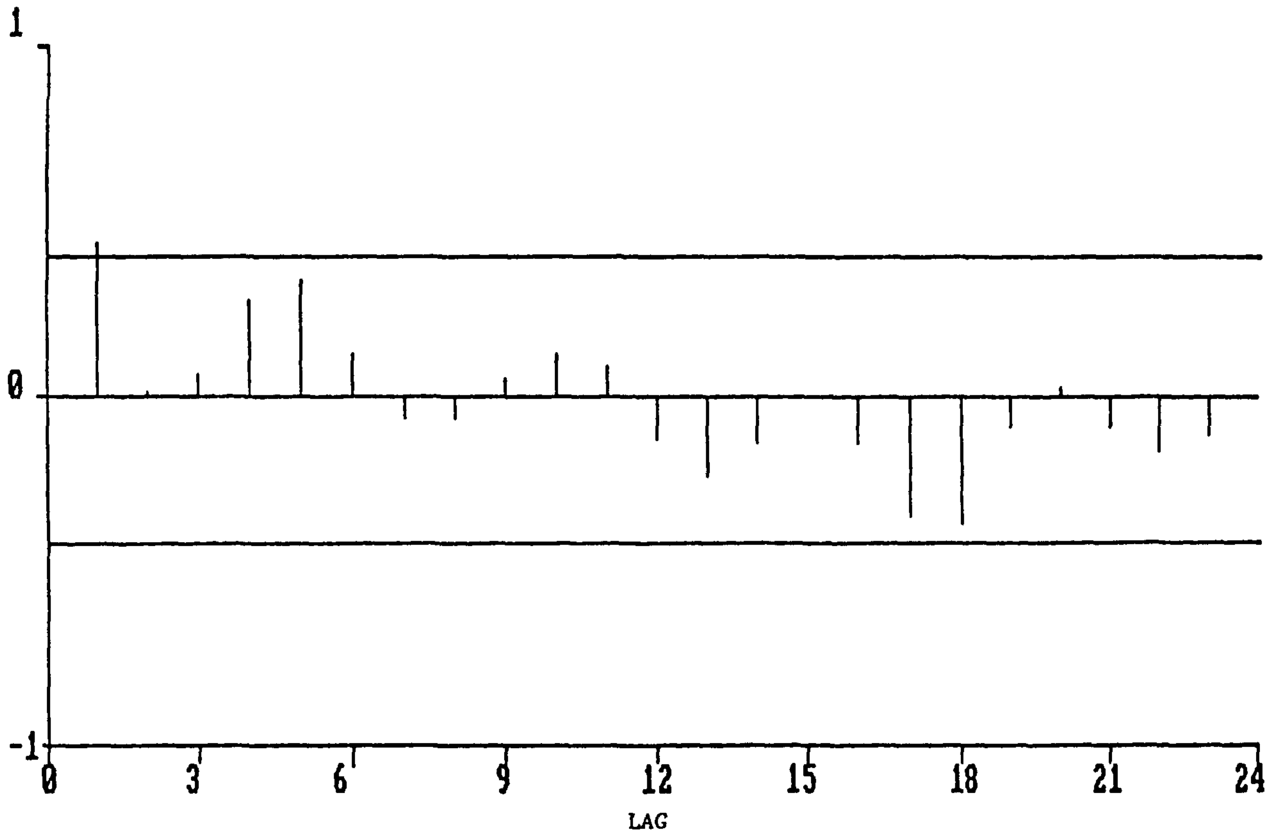


Figure 4-20. Correlogram of sulfate/ANC ratios shown in Figure 4-19.

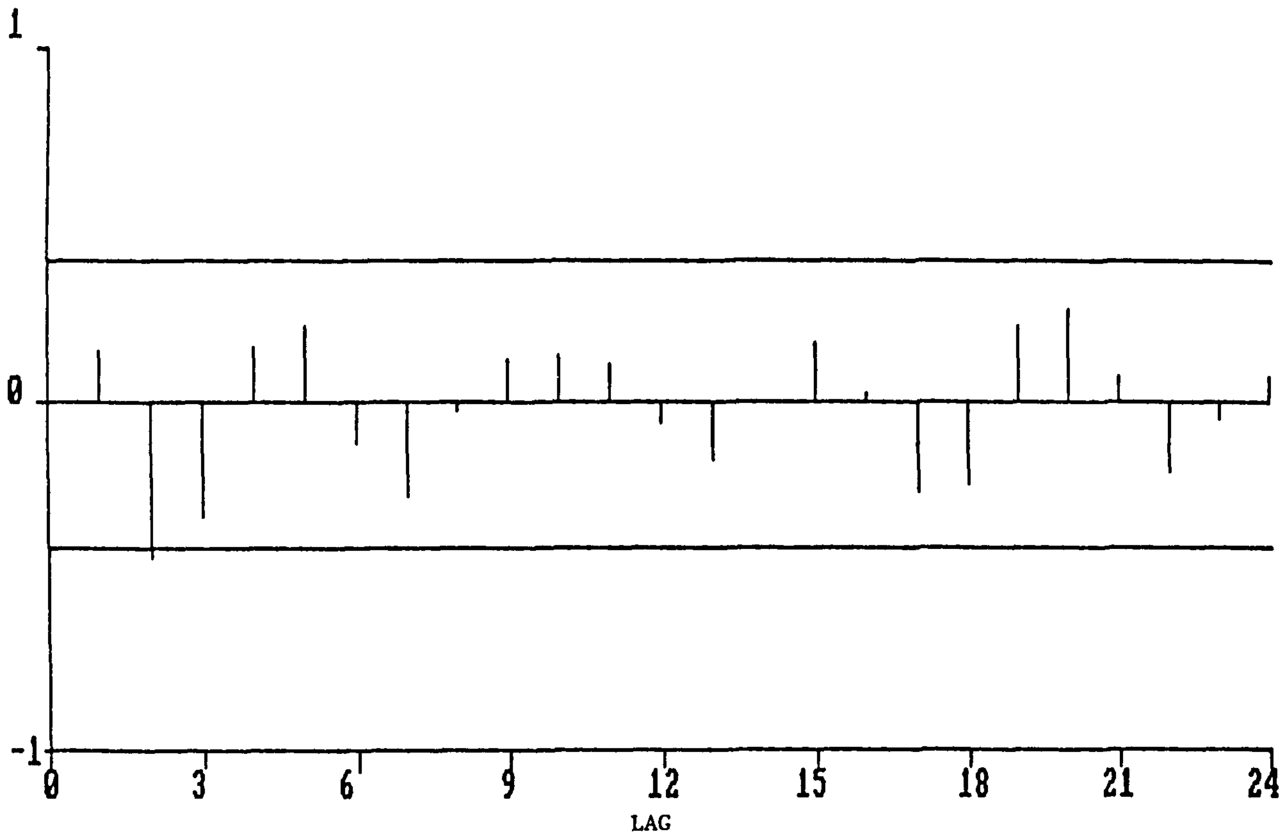


Figure 4-21. Correlogram of sulfate/ANC ratios shown in Figure 4-19 after detrending by ordinary least squares.

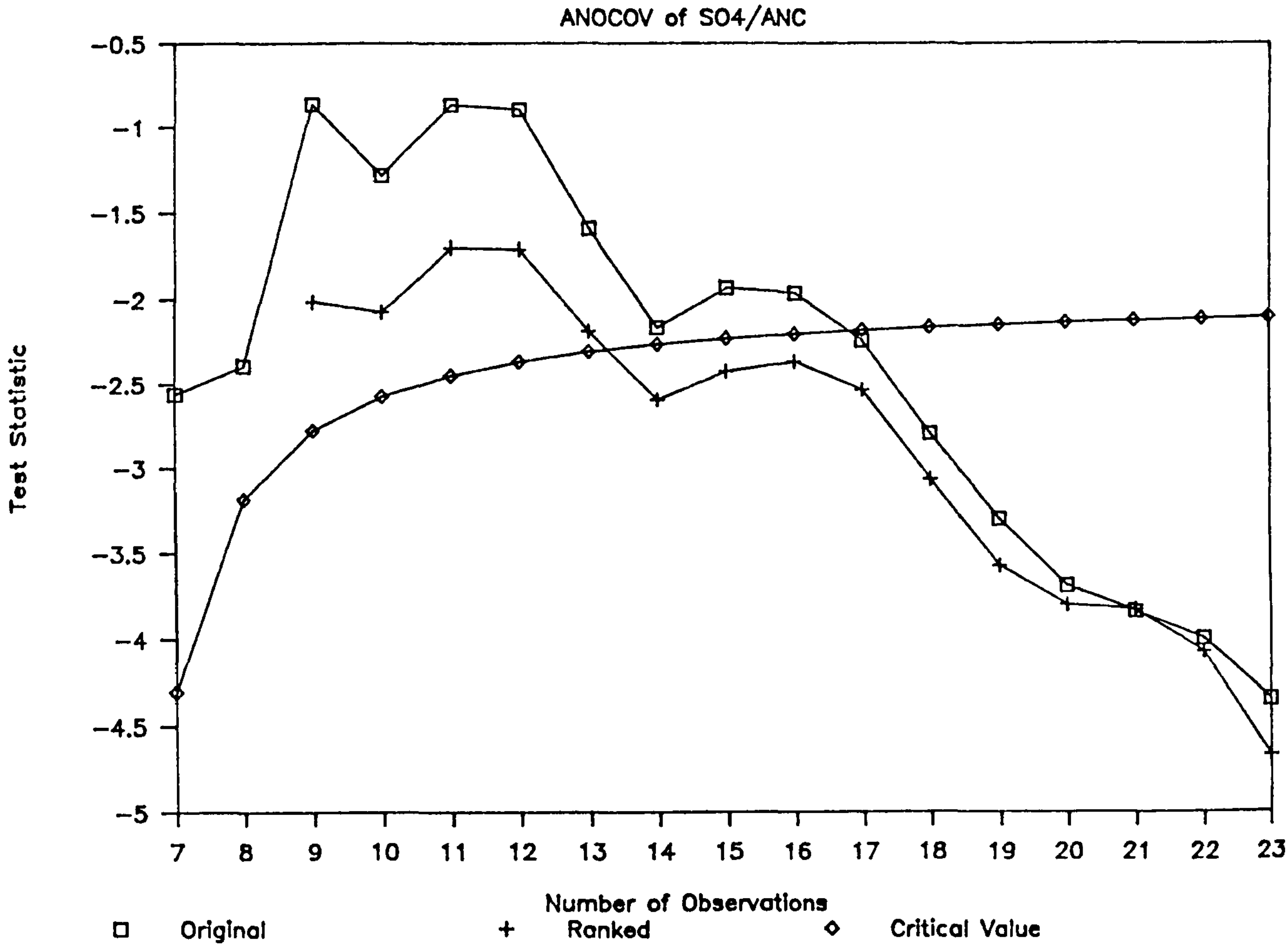


Figure 4-22. Results of ANCOV on raw sulfate/ANC ratios and on ranks of sulfate/ANC ratios. Critical value of the test statistic is shown for each number of observations. The test is significant when the calculated statistic is more negative than the critical value.

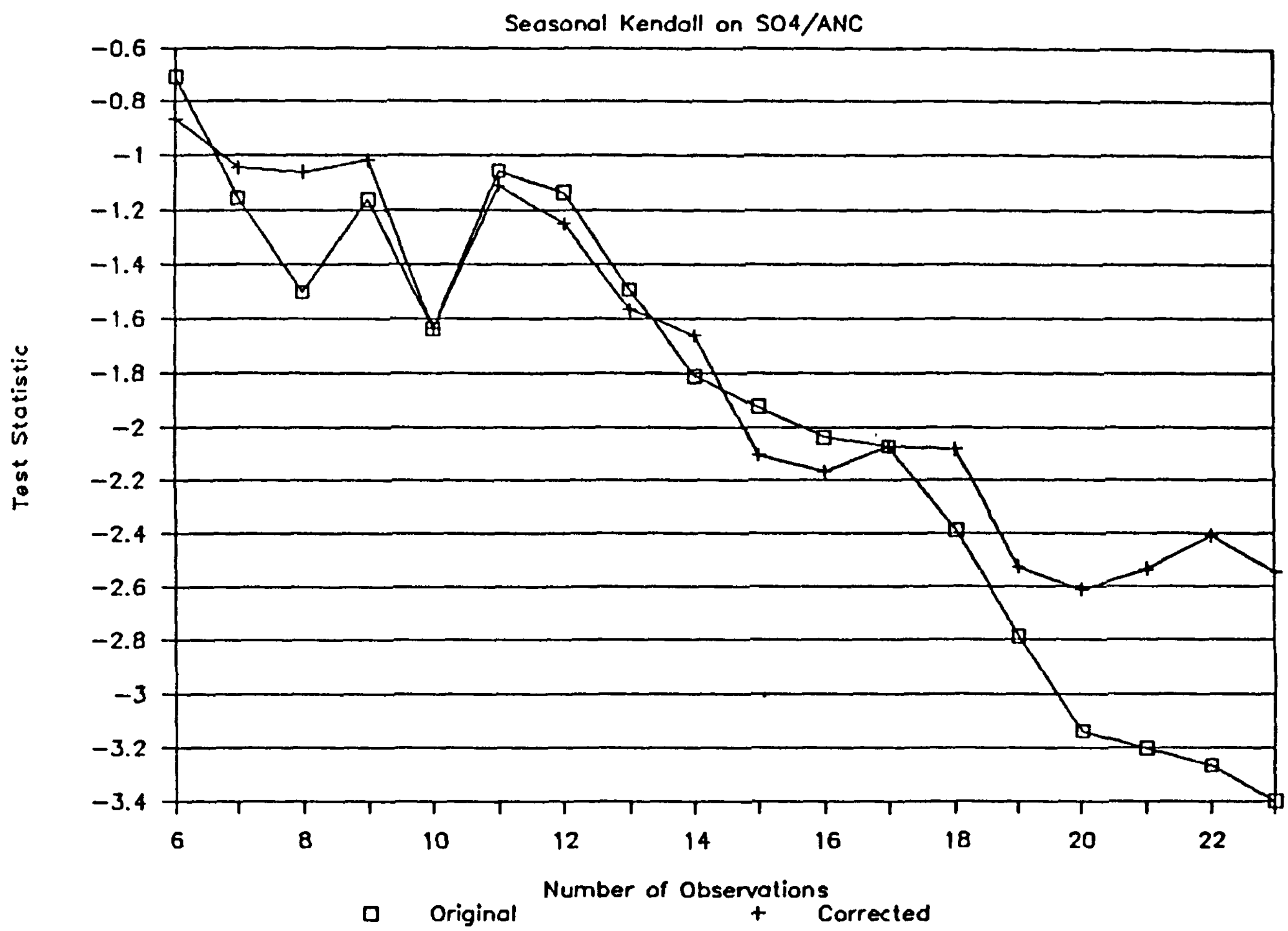


Figure 4-23. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw sulfate/ANC ratios.

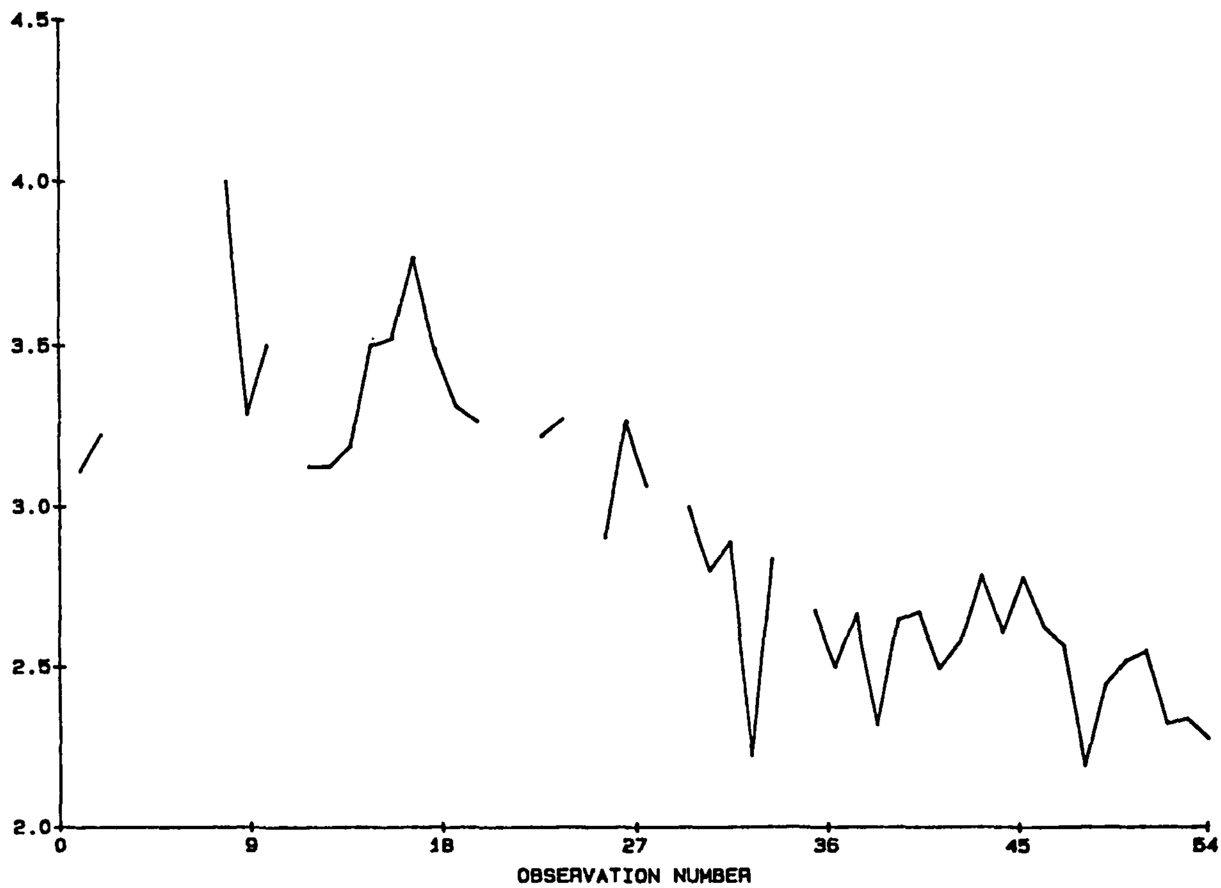


Figure 4-24. Quarterly sulfate/(calcium + magnesium) ratios for Clearwater Lake, Ontario, beginning fall of 1980.

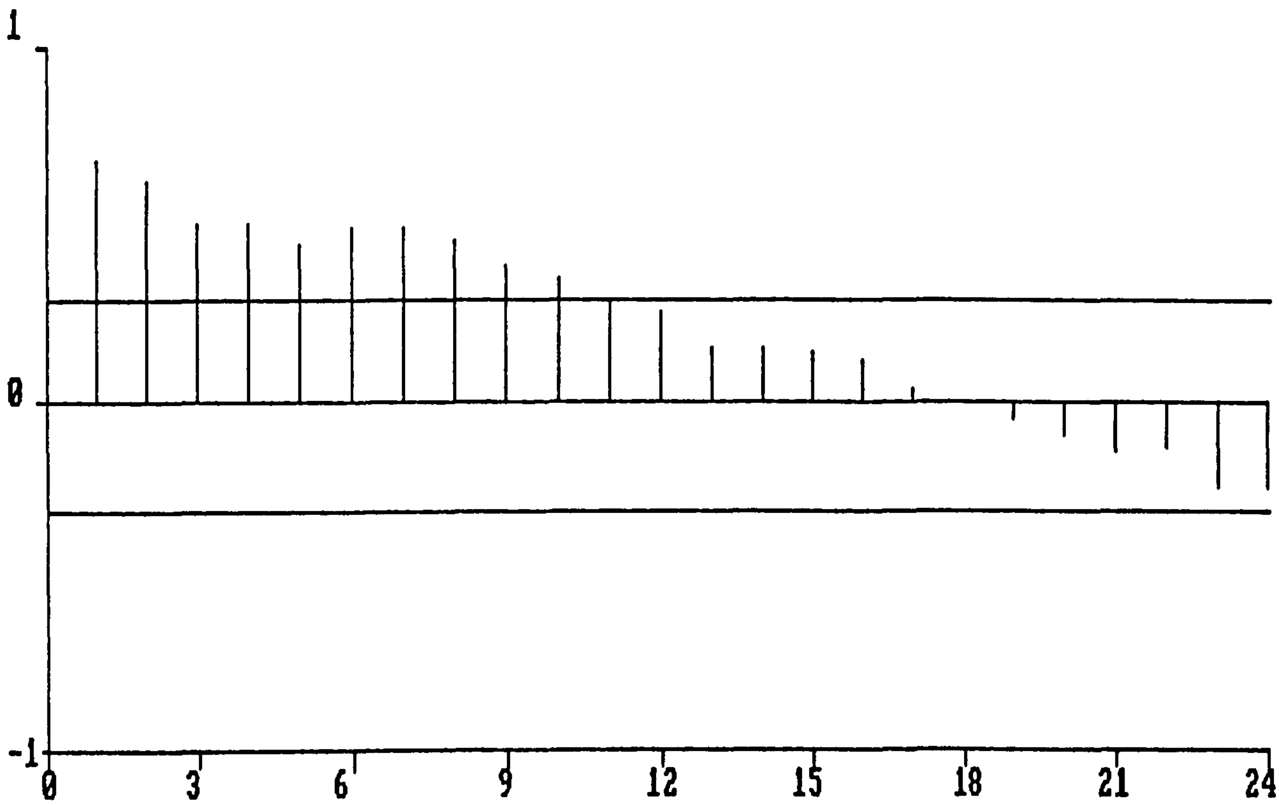


Figure 4-25. Correlogram of sulfate/(calcium + magnesium) ratios shown in Figure 4-24.

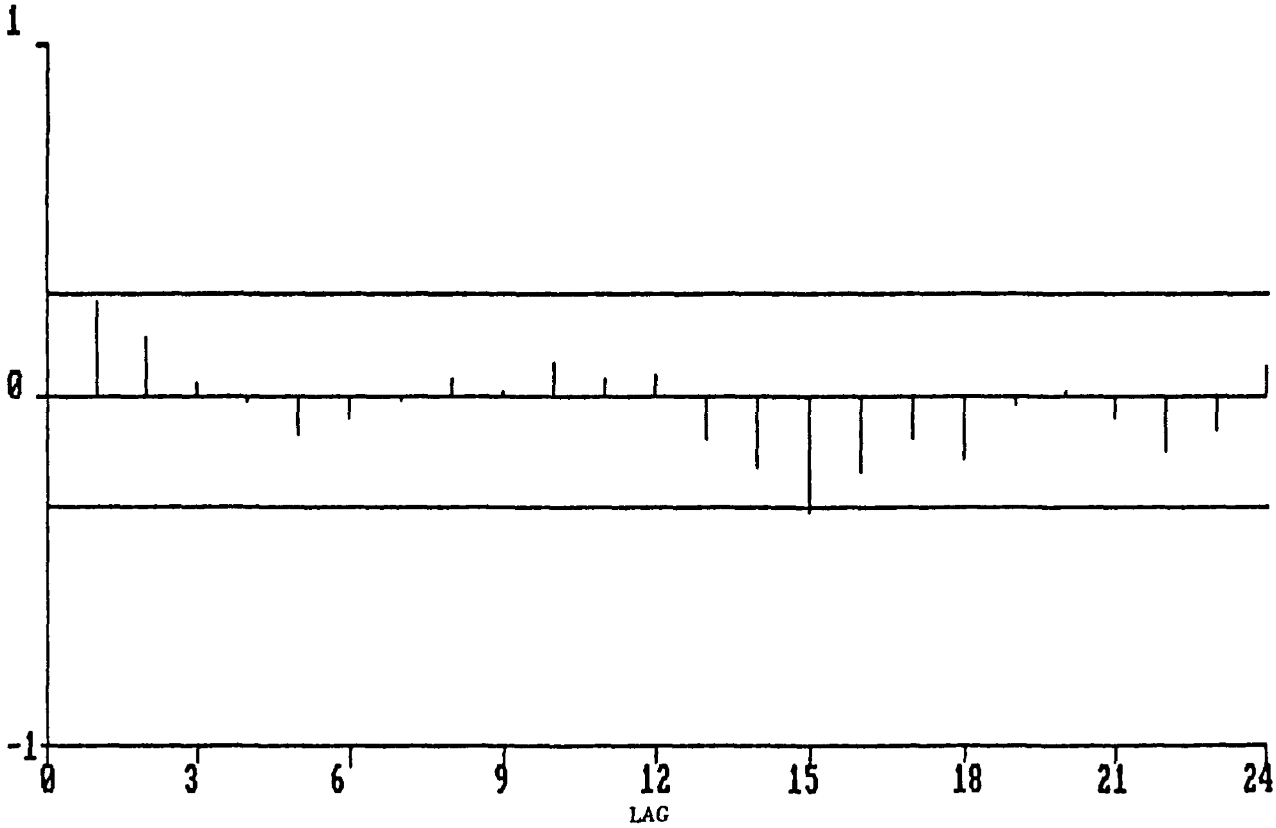


Figure 4-26. Correlogram of sulfate/(calcium + magnesium) ratios shown in Figure 4-24 after detrending by ordinary least squares.

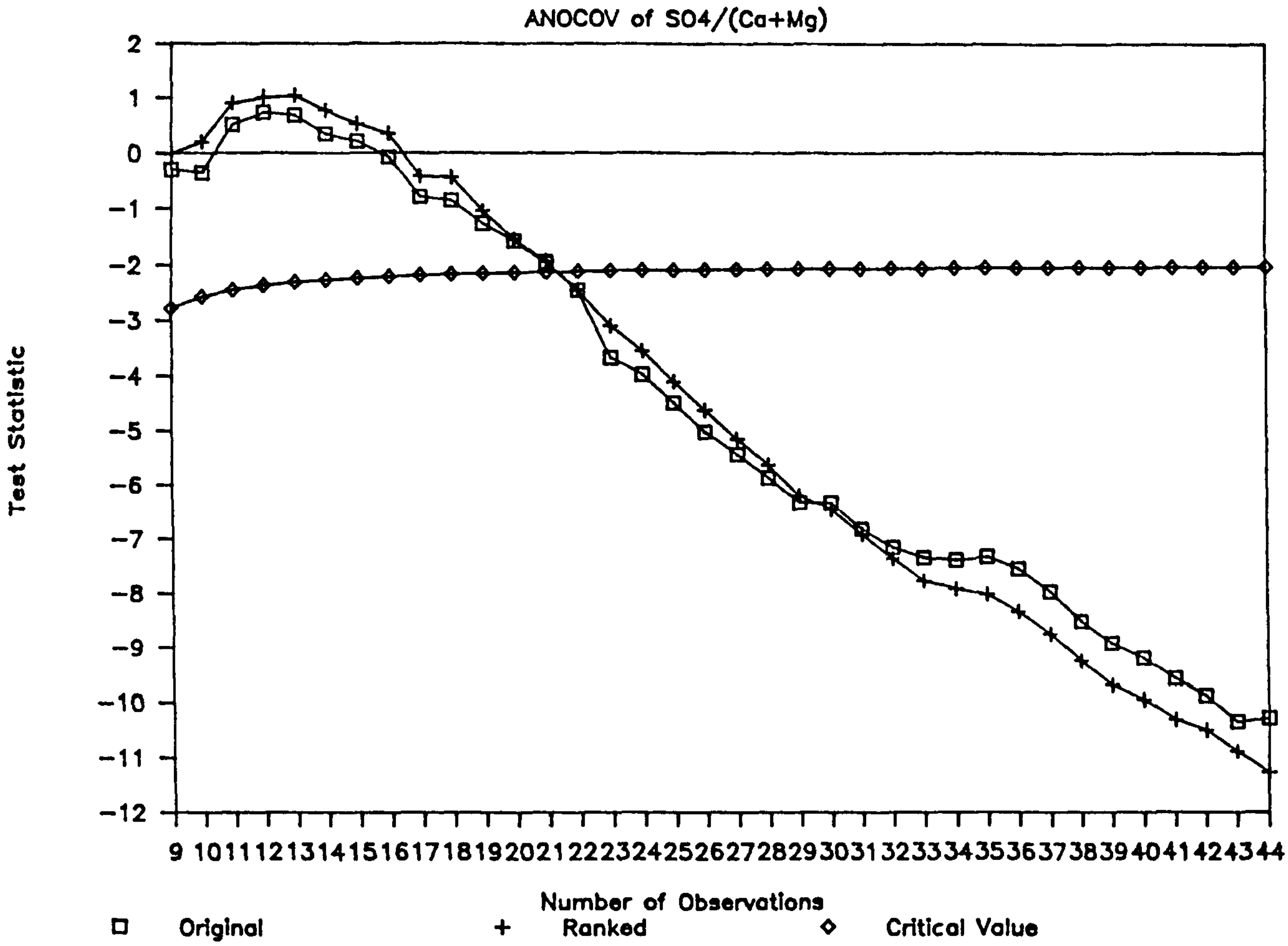


Figure 4-27. Results of ANOCOV on raw sulfate/(calcium + magnesium) ratios and on ranks of sulfate/(calcium + magnesium) ratios. Critical value of the test statistic is shown for each number of observations. The test is significant when the calculated statistic is more negative than the critical value.

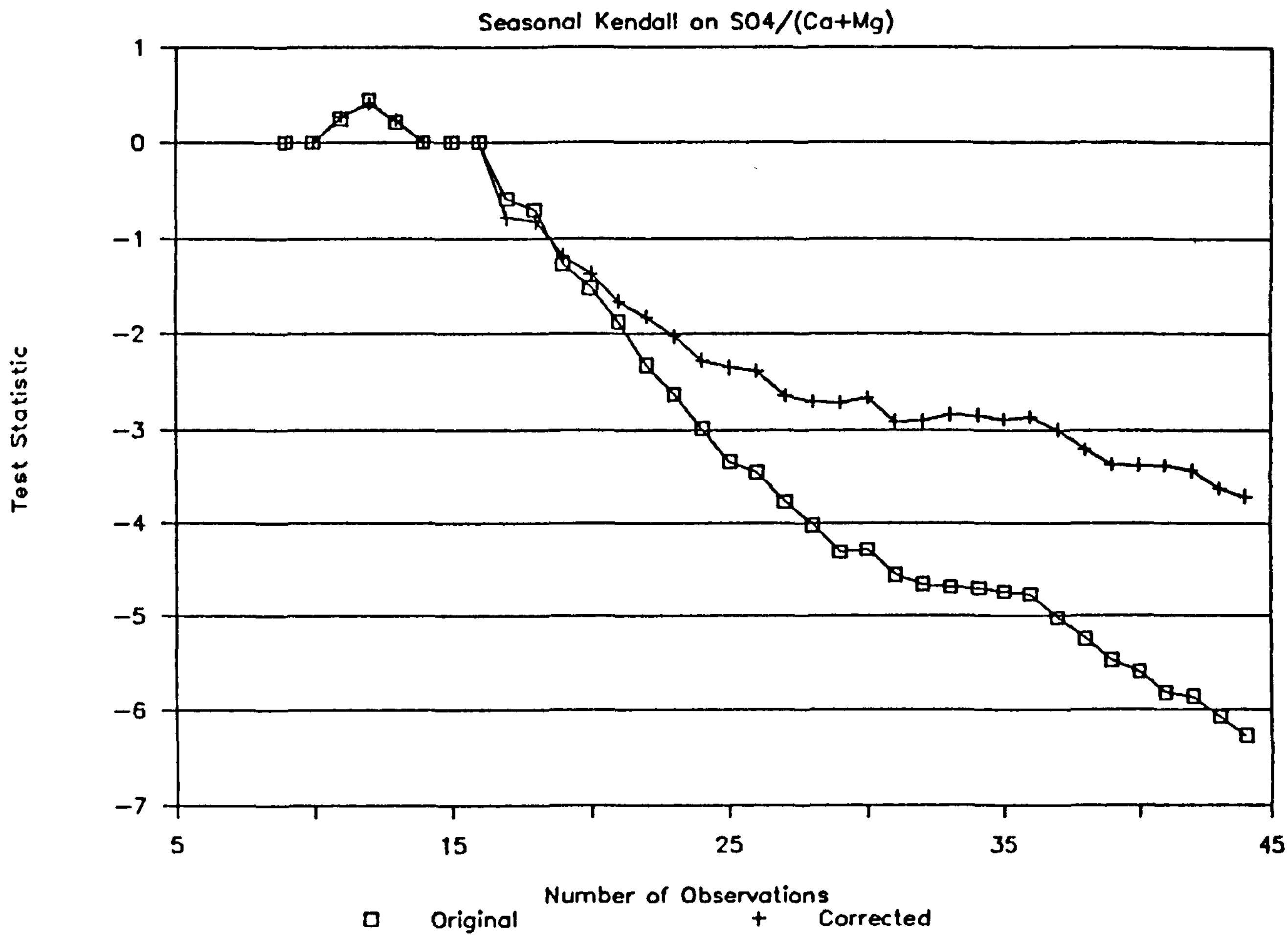


Figure 4-28. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw sulfate/(calcium + magnesium) ratios.

For the example data, there does not appear to be an advantage to using ratios for trend detection as opposed to individual variables. In other situations, ratios may be advantageous for detection and/or explanation of trends.

For the large trends seen here, ANOCOV on rank appears to work as well as ANOCOV on raw data. The correlation-corrected version of the SK test detects trends one or two observations later than the uncorrected version.

As stated earlier, the case study illustrates that proposed tests for trend will work well for large trends and time periods of four or more years. All of the test statistics were subject to large variability in shorter data records. For this example, there was little difference in performance among the tests studied.

4.3.1.6 Effect of Time of Sampling on Trend Detection, Quarterly Sampling--

For the Clearwater Lake data, the timing of sample collection has a notable effect on the length of time required to detect trends in sulfate. This may be illustrated by redefining quarters as (1) January, February, March, (2) April, May, June, etc., and choosing new data points closest to the center of these redefined quarters. Figures 4-29 and 4-30 show the results of applying ANOCOV and SK tests on the new series. In both cases, trends become significant two or more quarters later than with the original data. Figure 4-31 presents the least squares regression slope of the entire sulfate series as a function of length of record. Results are highly variable for the first five years or so, but later stabilize around a value of 1.0 to 1.1 mg L^{-1}/year.

For ANC, the redefined quarters do not affect the point at which trend becomes significant using either ANOCOV or SK tests (Figures 4-32 and 4-33). However the SK test statistic remains significant after 13 quarters in the new data series, whereas it temporarily dips and becomes not significant in the original series. Figure 4-34 indicates that after year two, the regression slope varies between 0.13 and 0.18 mg L^{-1}/year over the historical record.

We emphasize that seasons should be defined hydrologically or limnologically and could be much shorter or longer than three months. A season could be defined in terms of streamflow (spring freshet for example) or lake temperature profile rather than calendar date. The recommended trend testing procedures would not be greatly affected by using sampling intervals that were shorter or longer than three months or that varied somewhat from year to year, as long as consideration was restricted to a fixed number of seasons per year and one observation per season.

For the ANOCOV procedure, a day number could be used rather than an observation number for the time variable, t. This substitution would better reflect the exact time at which a given sample was collected but would probably not have much impact on trend testing results.

4.3.1.7 Trend Detection, Annual Sampling--

In some, perhaps many, cases it may be desirable to collect a single spring or fall sample rather than four quarterly samples. In order to determine whether annual sampling could detect trends quickly, a simple study was performed using the Clearwater data set to obtain both spring and fall annual series. Seasons were defined using limnological characteristics of lakes as opposed to quarters. Table 4-3 presents the results of annual subsampling of the Clearwater Lake data set, taking the ANC and sulfate observations closest to May 15 (spring). Table 4-4 repeats the exercise, in each case taking the observation closest to November 7.

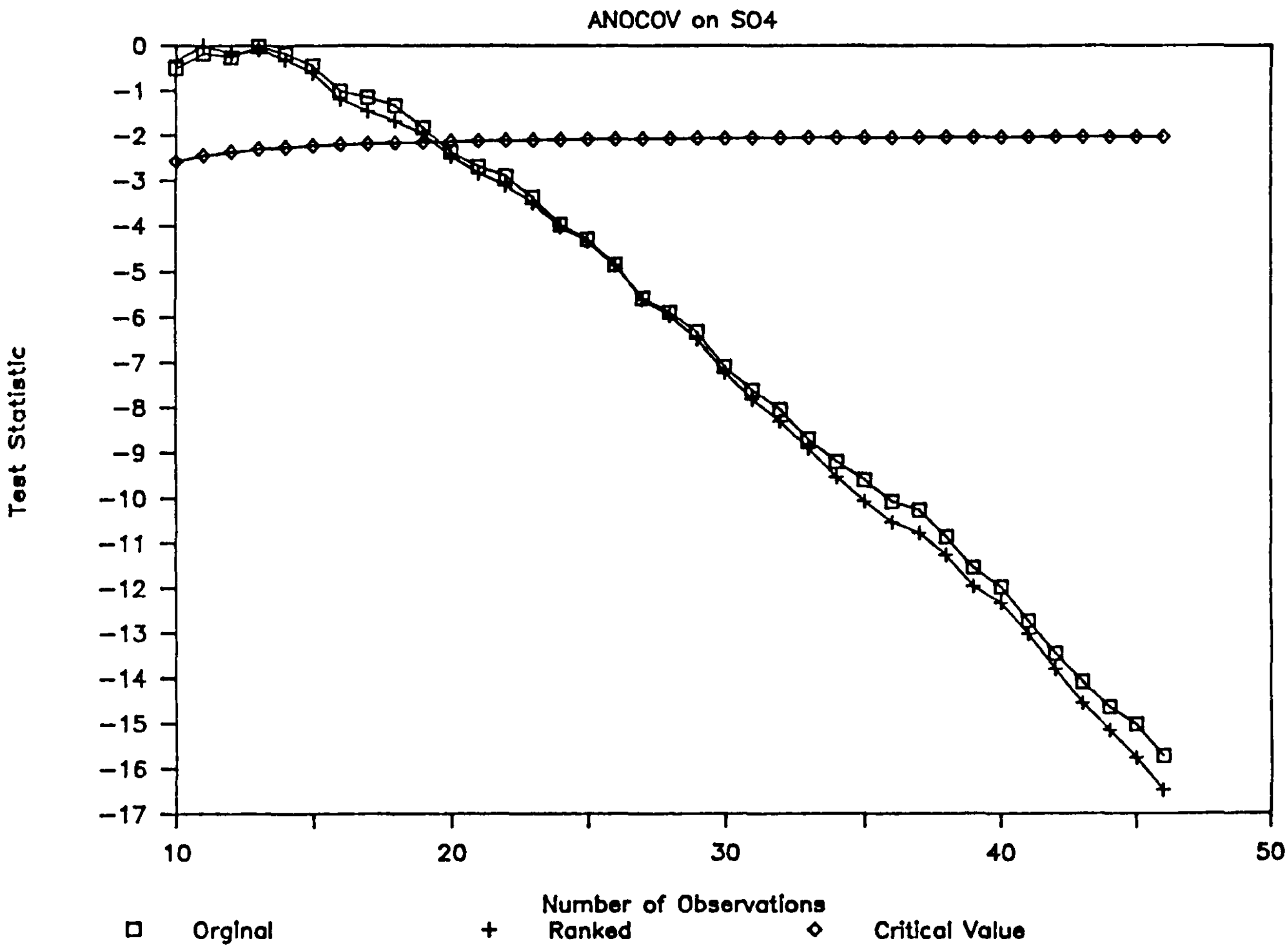


Figure 4-29. Results of ANOCOV on raw sulfate data with quarters redefined as Jan.-Mar., Apr.-June, etc., rather than Dec.-Feb., etc.

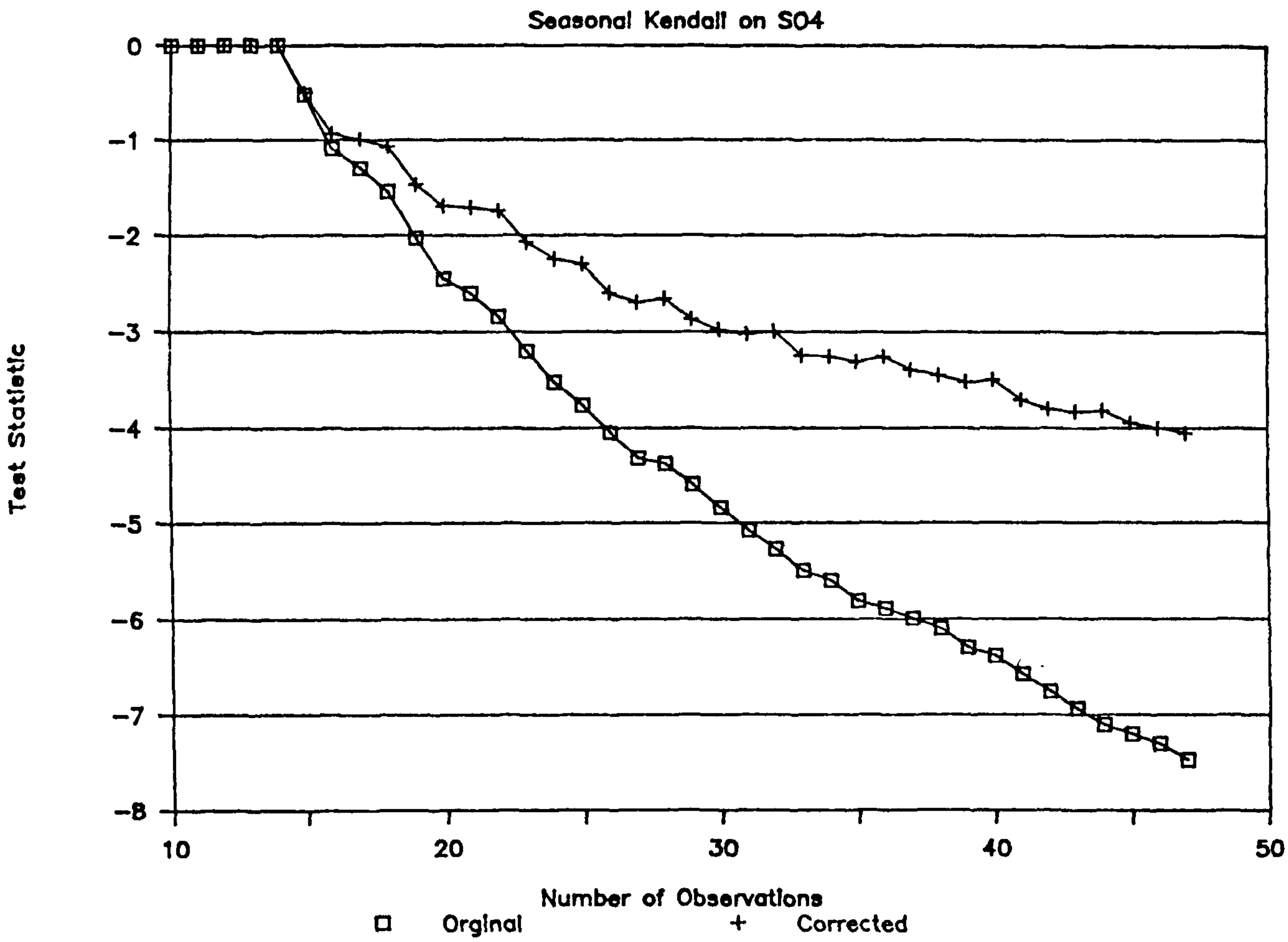


Figure 4-30. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw sulfate data with quarters redefined as in Figure 4-29.

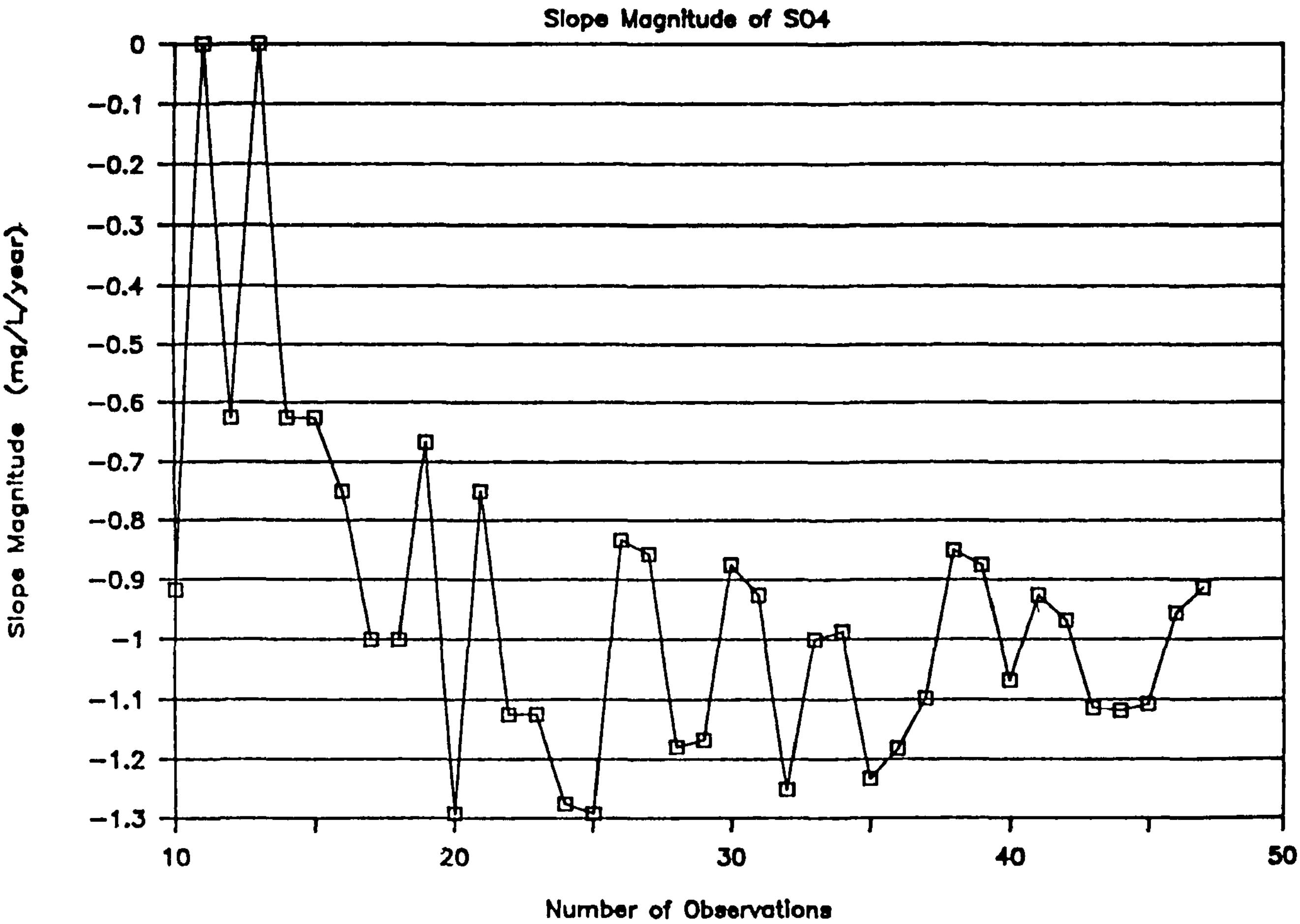


Figure 4-31. Least squares regression slope of the entire sulfate series as a function of length of record.

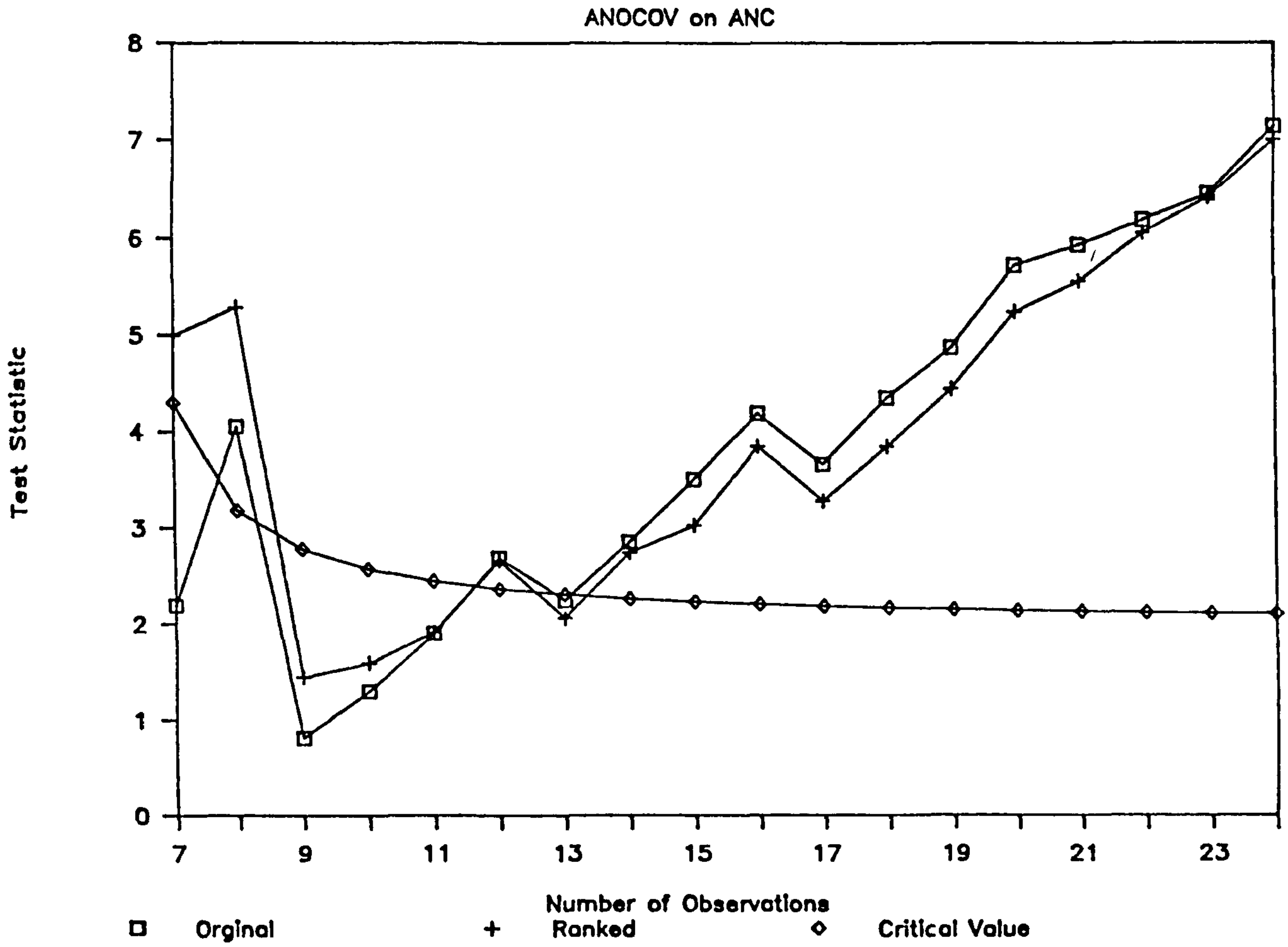


Figure 4-32. Results of ANOCOV on raw ANC data with quarters redefined as Jan.-Mar., Apr.-June, etc., rather than Dec.-Feb., etc.

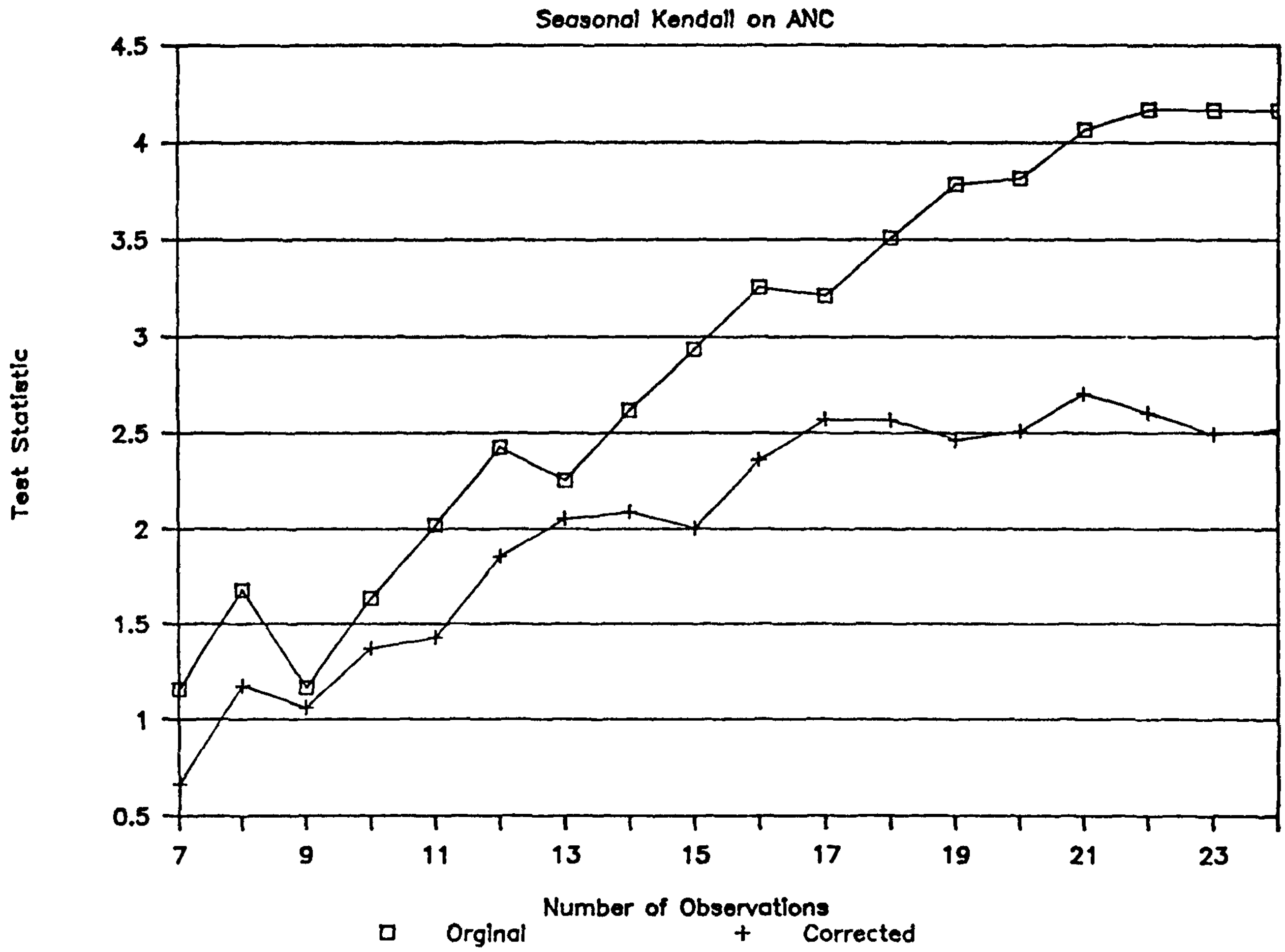


Figure 4-33. Results of seasonal Kendall (square symbols) and seasonal Kendall corrected for serial correlation (plus symbols) on raw ANC data with quarters redefined as in Figure 4-32.

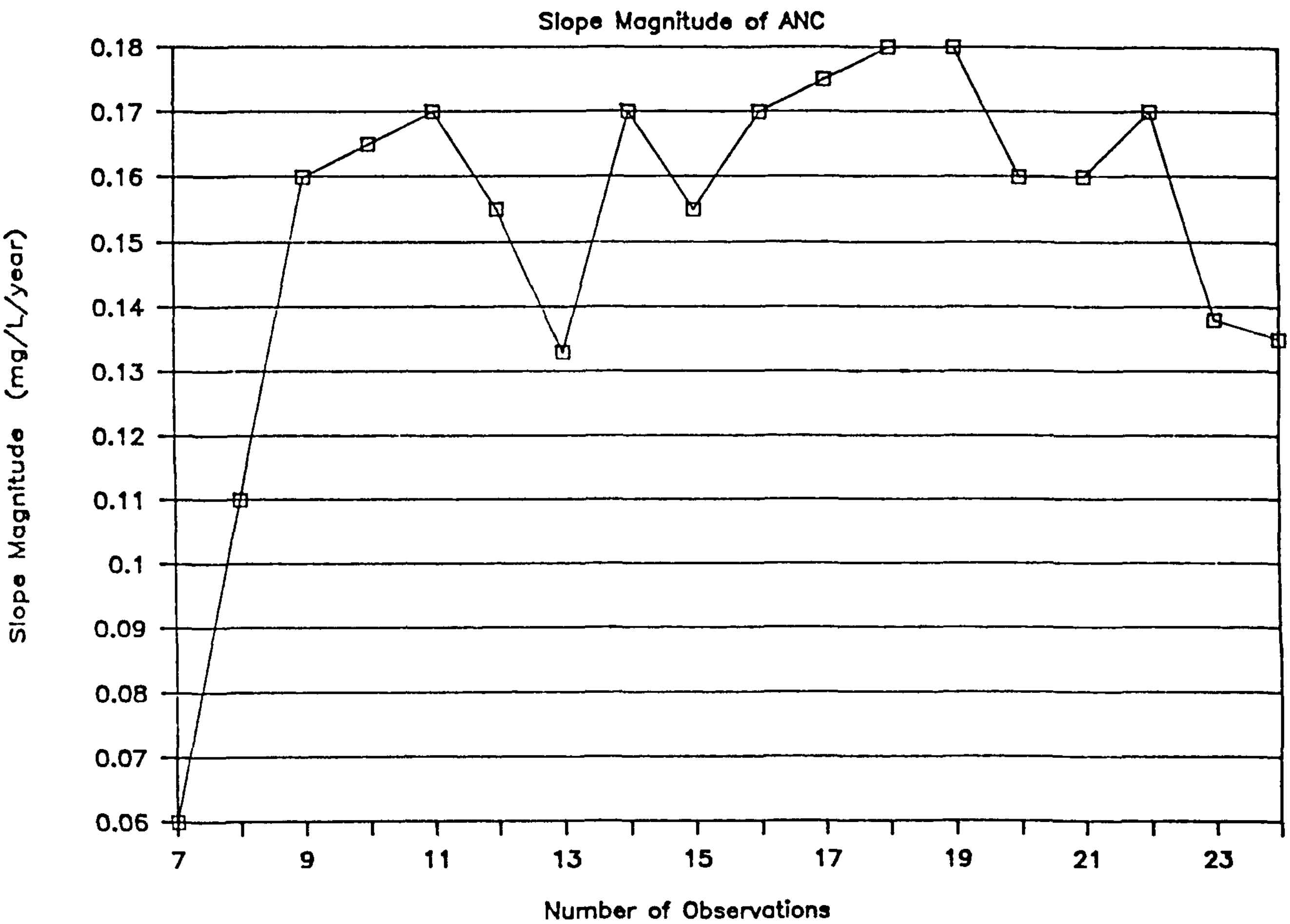


Figure 4-34. Least squares regression slope of the entire ANC series as a function of length of record.

TABLE 4-3. RESULTS OF TREND DETECTION WITH ANNUAL SPRING SUBSAMPLING OF ANC AND SULFATE AT CLEARWATER LAKE, ONTARIO

SPRING ANC

DATE	OBSERVATION VALUE mg L^{-1} as $CaCo_3$	KENDALL TAU Test Statistic	KENDALL TAU Critical Value	Significant Trend at 5% Two-sided Test?
5/13/81	-1.72	--	--	
5/13/82	-1.56	--	--	
5/02/83	-1.21	--	--	
5/08/84	-1.21	6	6	Yes
5/22/85	-0.87	10	8	Yes
5/07/86	-1.00	13	11	Yes

SPRING SULFATE

DATE	OBSERVATION VALUE mg L^{-1}	KENDALL TAU Test Statistic	KENDALL TAU Critical Value	Significant Trend at 5% Two-sided Test?
5/19/75	24.00	--	--	
5/11/76	23.50	--	--	
5/10/77	26.00	--	--	
5/11/78	23.50	--	--	No
5/02/79	21.50	-4	-8	No
5/12/80	21.00	-9	-11	No
5/13/81	19.80	-15	-13	Yes
5/13/82	19.80	-20	-16	Yes
5/02/83	17.63	-28	-18	Yes
5/08/84	18.93	-35	-21	Yes
5/22/85	15.05	-45	-25	Yes
5/07/86	16.60	-54	-28	Yes

TABLE 4-4. RESULTS OF TREND DETECTION WITH ANNUAL FALL SUBSAMPLING OF ANC AND SULFATE AT CLEARWATER LAKE, ONTARIO

FALL ANC

DATE	OBSERVATION VALUE mg L^{-1} as $CaCo_3$	KENDALL TAU Test Statistic	KENDALL TAU Critical Value	Significant Trend at 5% Two-sided Test?
11/20/80	-2.20	--	--	
10/20/81	-2.14	--	--	
10/18/82	-1.83	--	--	
10/18/83	-1.36	6	6	Yes
11/07/84	-1.03	10	8	Yes
11/19/85	-1.10	13	11	Yes
11/11/86	-1.10	17	13	Yes

FALL SULFATE

DATE	OBSERVATION VALUE mg L^{-1}	KENDALL TAU Test Statistic	KENDALL TAU Critical Value	Significant Trend at 5% Two-sided Test?
11/11/75	21.00	--	--	
10/26/76	27.00	--	--	
10/17/77	26.00	--	--	
11/09/78	24.00	--	--	No
11/01/79	22.50	-2	-8	No
10/30/80	21.00	-5	-11	No
10/20/81	21.00	-7	-13	No
10/18/82	19.40	-14	-16	No
10/18/83	18.86	-22	-18	Yes
11/07/84	17.00	-31	-21	Yes
11/19/85	16.75	-41	-25	Yes
11/11/86	16.59	-52	-28	Yes

Dates of observations are shown in the tables, with results of the Kendall-tau test for trend on the annual values. For sulfate, trend is detected after seven years in the spring data and nine years in the fall data. For ANC, trend is significant after four years, using the spring data, and is also significant in the fall data after four years. Figures 4-35 through 3-38 are time series plots of the annual (later winter and fall) ANC and sulfate data.

4.3.2 Twin Lakes, Colorado

A similar but less detailed study was performed on ANC data from Twin lakes, Colorado (Sartoris, 1987). Quarterly data were used with quarters defined as (1) December, January, February, (2) March, April, May, etc. Quarterly observations were obtained as subsamples from a series of monthly means for the period January 1977 to September 1985. All samples were depth integrated, and units are mg L^{-1} as bicarbonate. Station 2 was the middle of Lower Twin Lakes and Station 4 was the middle of Upper Twin Lakes.

The quarterly time series of Figure 4-39 for Station 2 shows a generally decreasing trend over the period; ANOCOV results (Figure 4-40) and SK results (Figure 4-41) confirm the statistical signficance of the trend. Using ANOCOV on ranks, the trend is significant for quarters 8 through 13 and 19 through 35. Using SK, the trend is significant for quarter 10 and quarters 20 through 35. The SK test with correction for serial correlation does not show a significant trend until quarter 24. A plot of regression slopes over time is presented in Figure 4-42.

Station 4 ANC data do not show a clear overall trend in the time series of Figure 4-43. Some short-term "trends" are, however, apparent. The ANOCOV test indicates a significant decreasing trend for quarters 7 through 12 and after quarter 22 (Figure 4-44). The SK test indicates significant trend at quarter 10 and for quarters 22 through 32 (Figure 4-45). Both SK and ANOCOV on ranks tests show that the overall trend through quarter 35 is not significant. Both tests agree with the results of visual inspection of data and with the plot of regression slopes over time (Figure 4-46). Since both tests identify significant short-term or temporary trends in the series, a logical extension of the analysis would be to attempt to explain the trends through analysis of other factors. Such extensions are discussed in the next section.

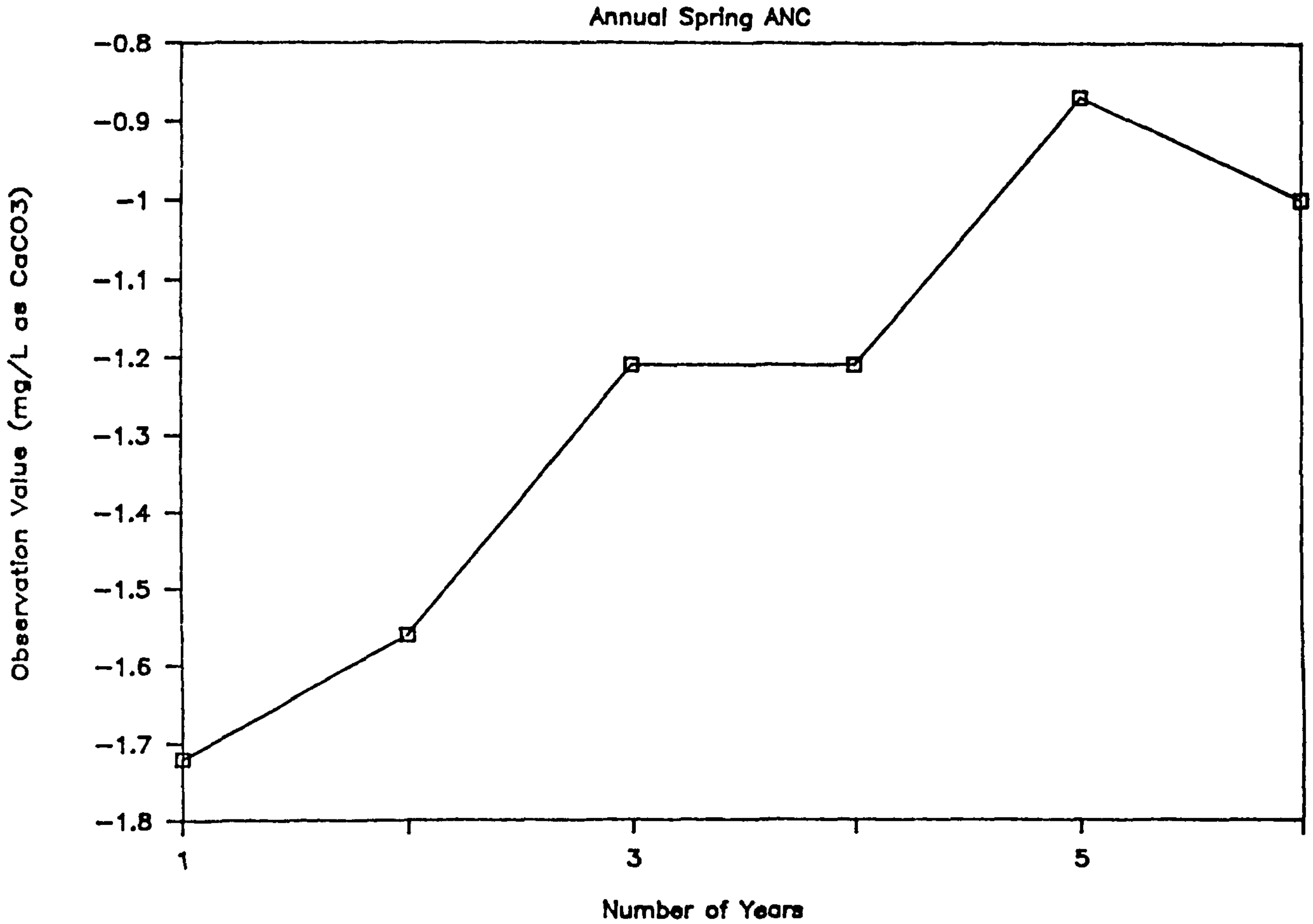


Figure 4-35. Time series plot of annual spring ANC at Clearwater Lake, Ontario.

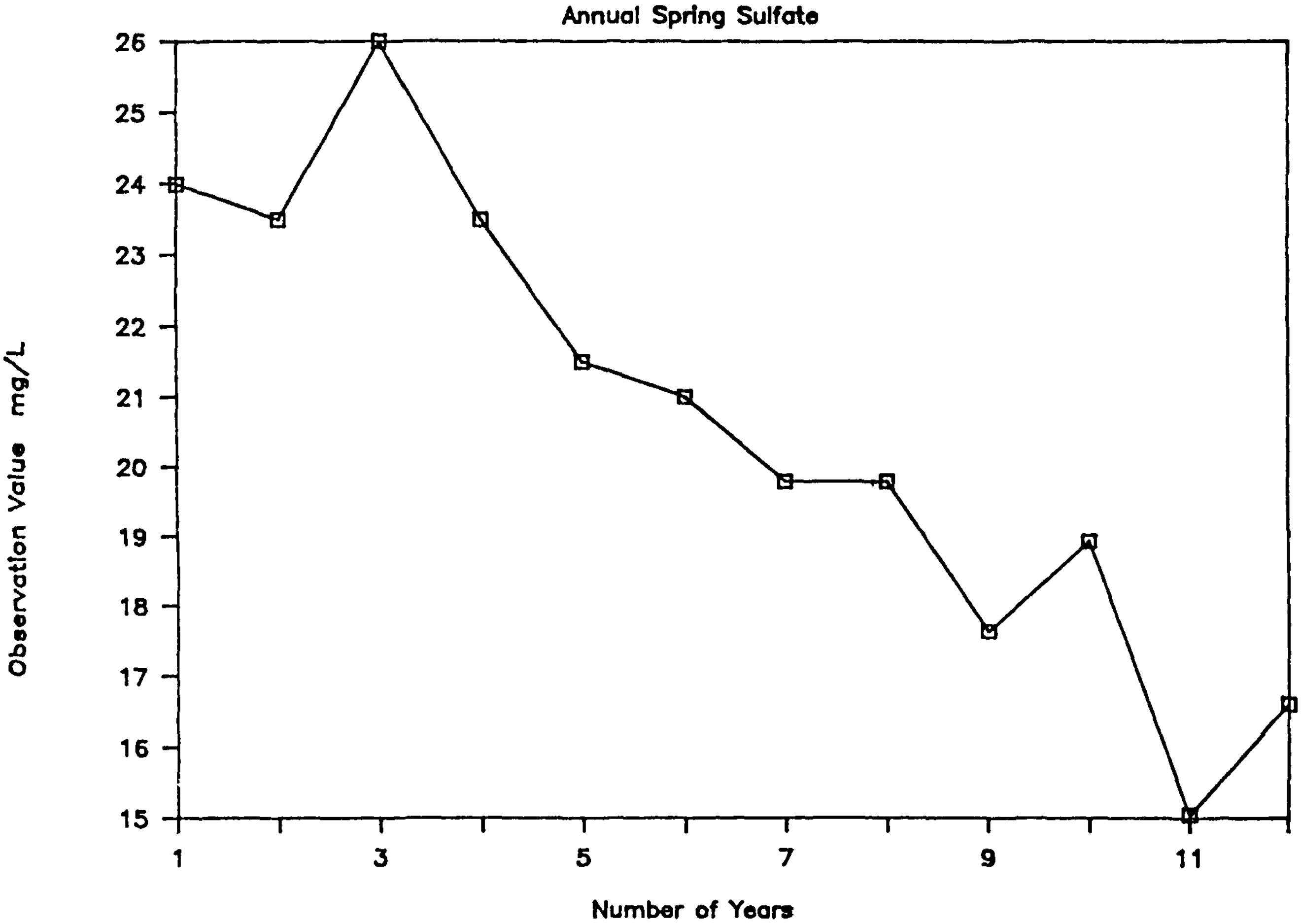


Figure 4-36. Time series plot of annual spring sulfate at Clearwater lake, Ontario.

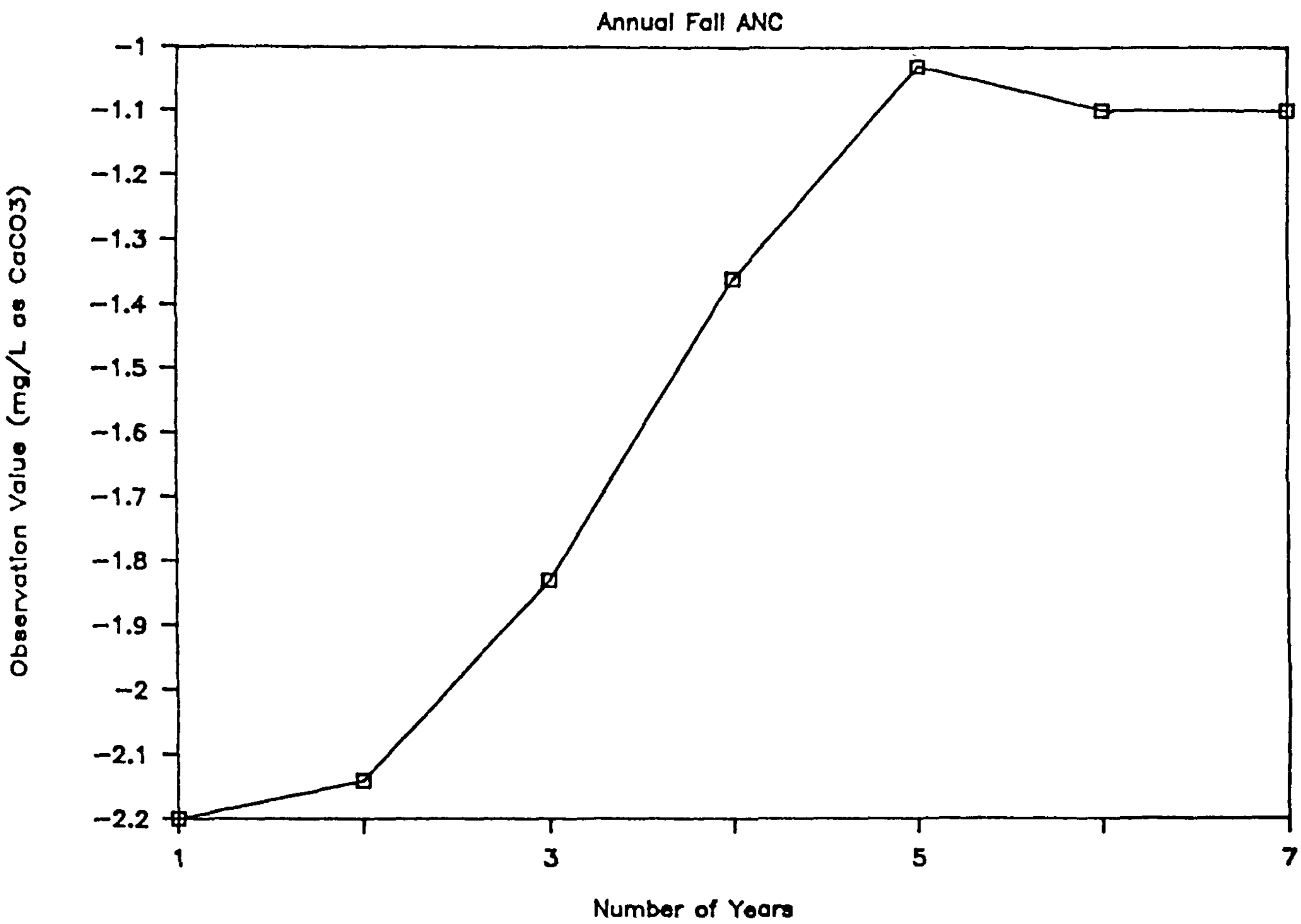


Figure 4-37. Time series plot of annual fall ANC at Clearwater Lake, Ontario.

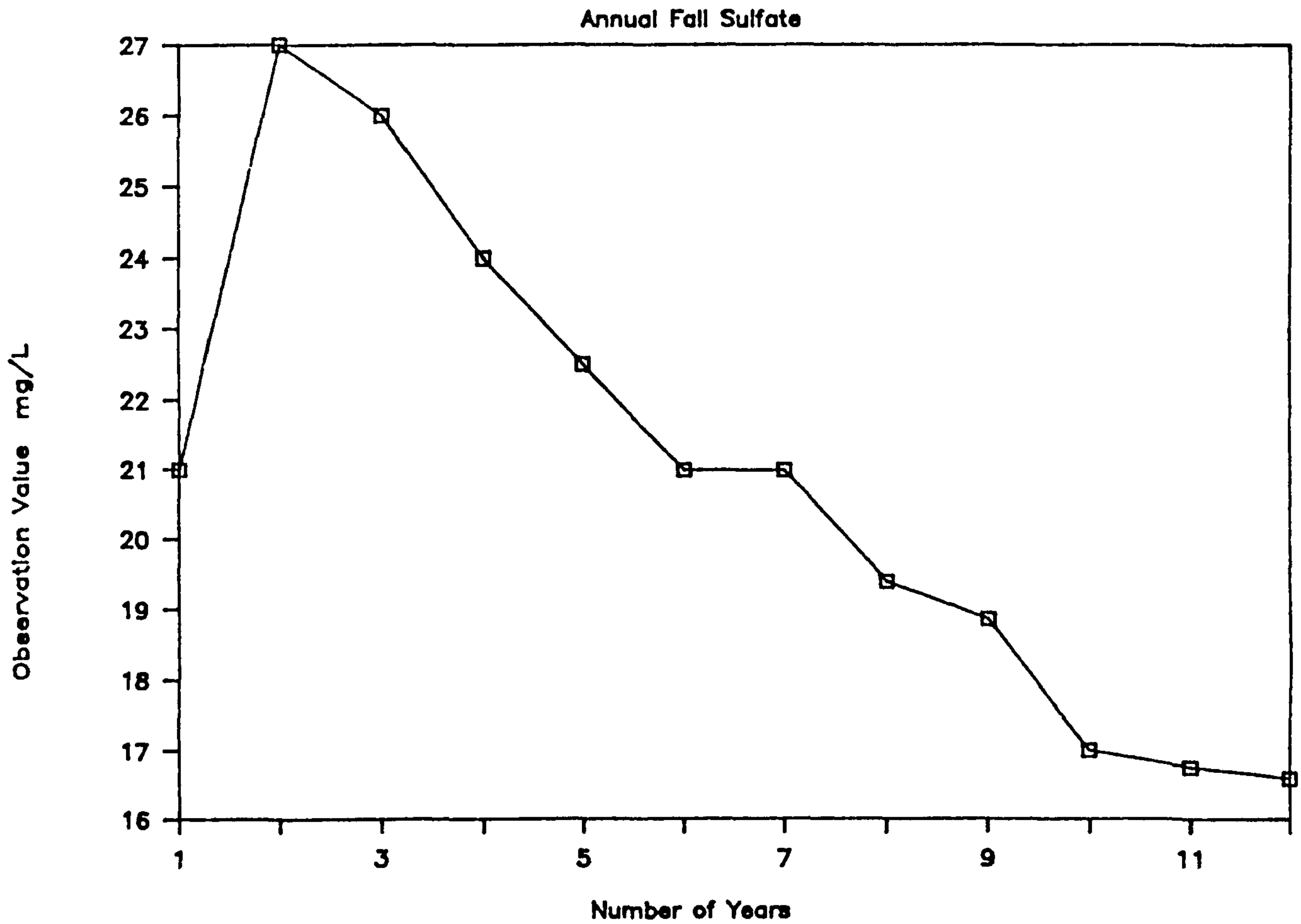


Figure 4-38. Time series plot of annual fall sulfate at Clearwater Lake, Ontario.

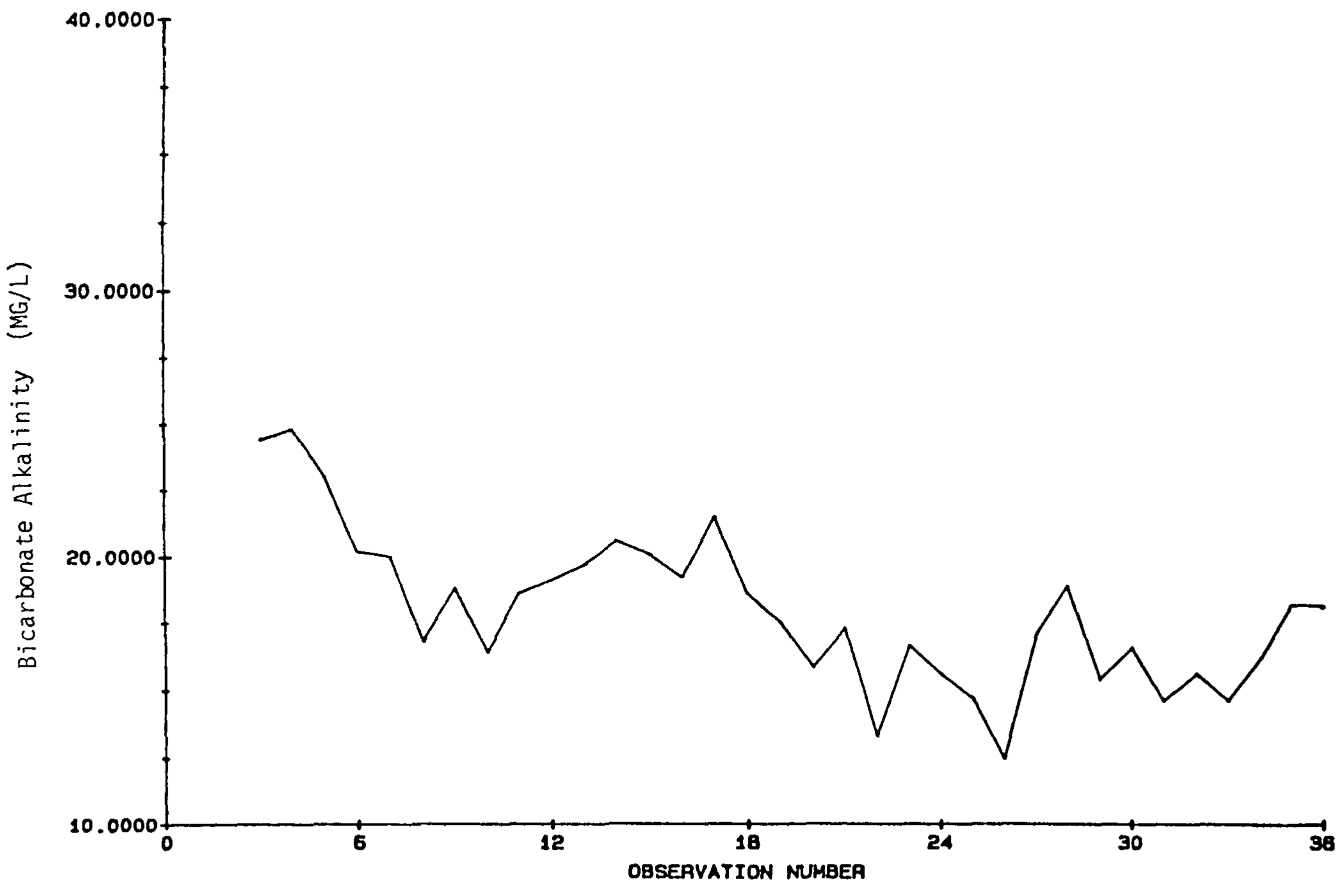


Figure 4-39. Quarterly time series of ANC data, in mg L^{-1} as bicarbonate, from Twin Lakes, Colorado, Station 2, beginning in January 1977.

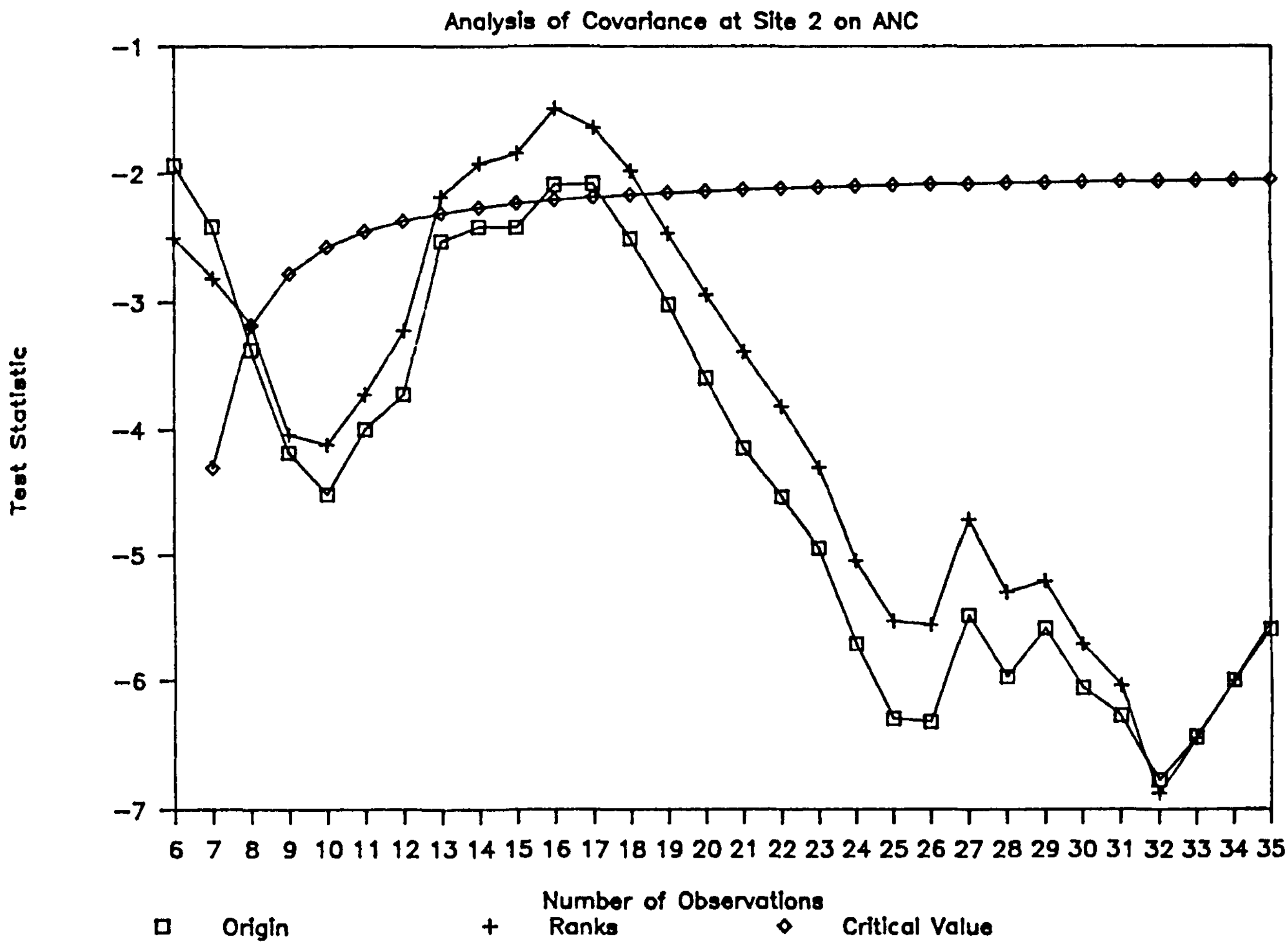


Figure 4-40. Results of ANOCOV on raw ANC and on ranks of ANC time series shown in Figure 4-39. Critical value of the test statistic in shown for each number of observations. The test is significant when the calculated statistic is more negative than the critical value.

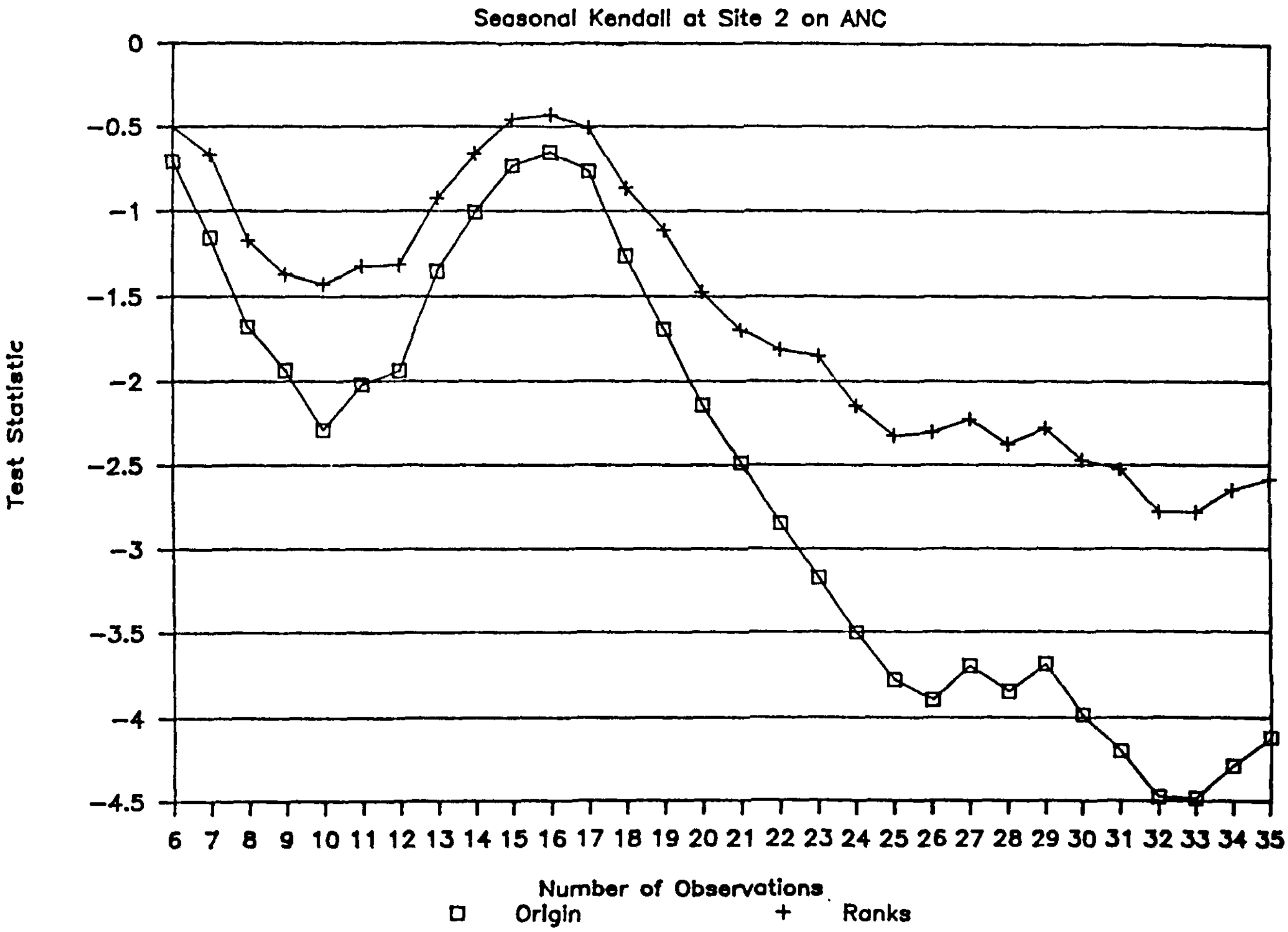


Figure 4-41. Results of seasonal Kendall (square symbols) and seasonal Kendall with correction for serial correlation (plus symbols) for raw ANC data shown in Figure 4-39.

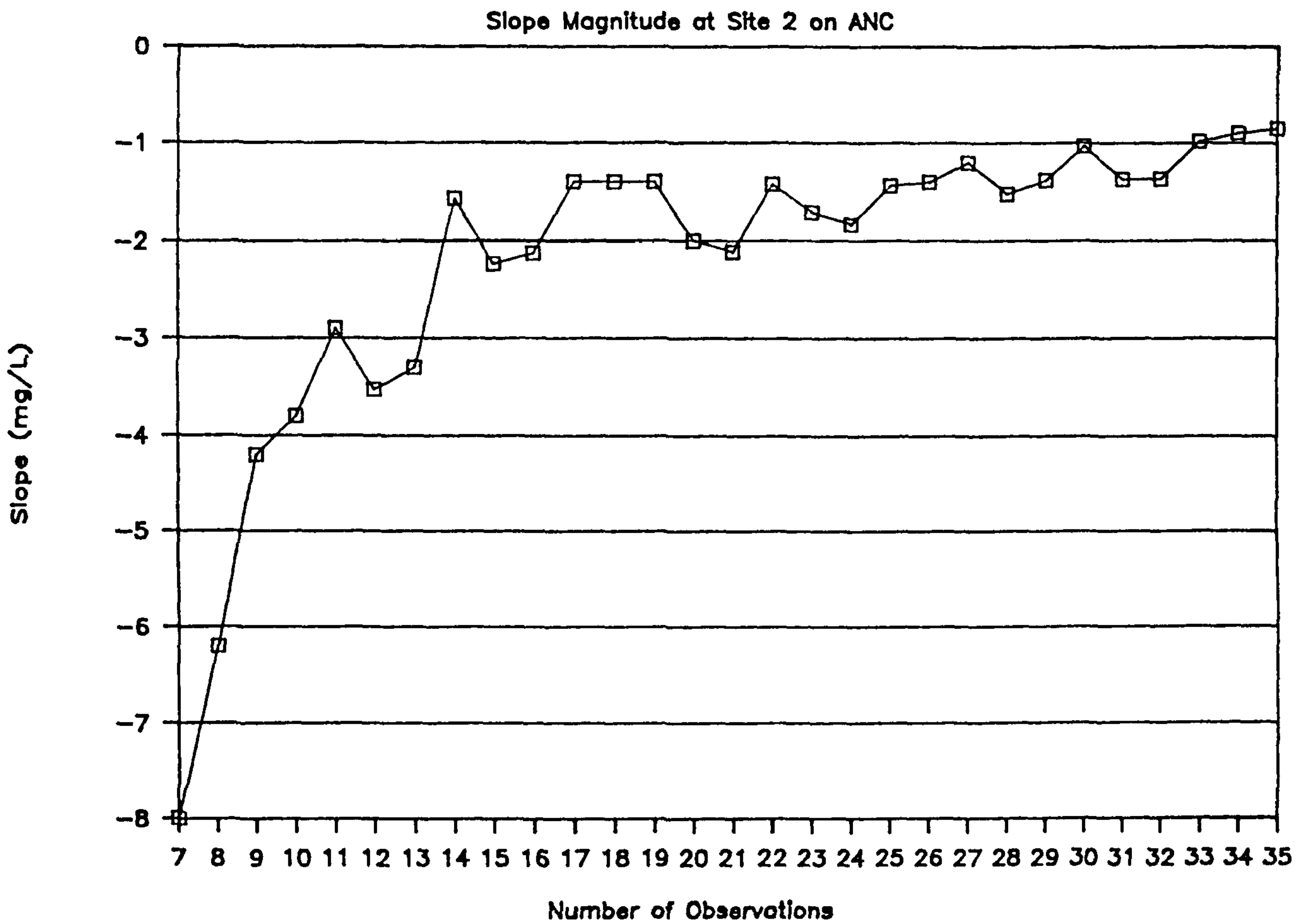


Figure 4-42. Least squares regression slope of the entire ANC series at Station 2 in Twin Lakes, Colorado, as a function of number of observations.

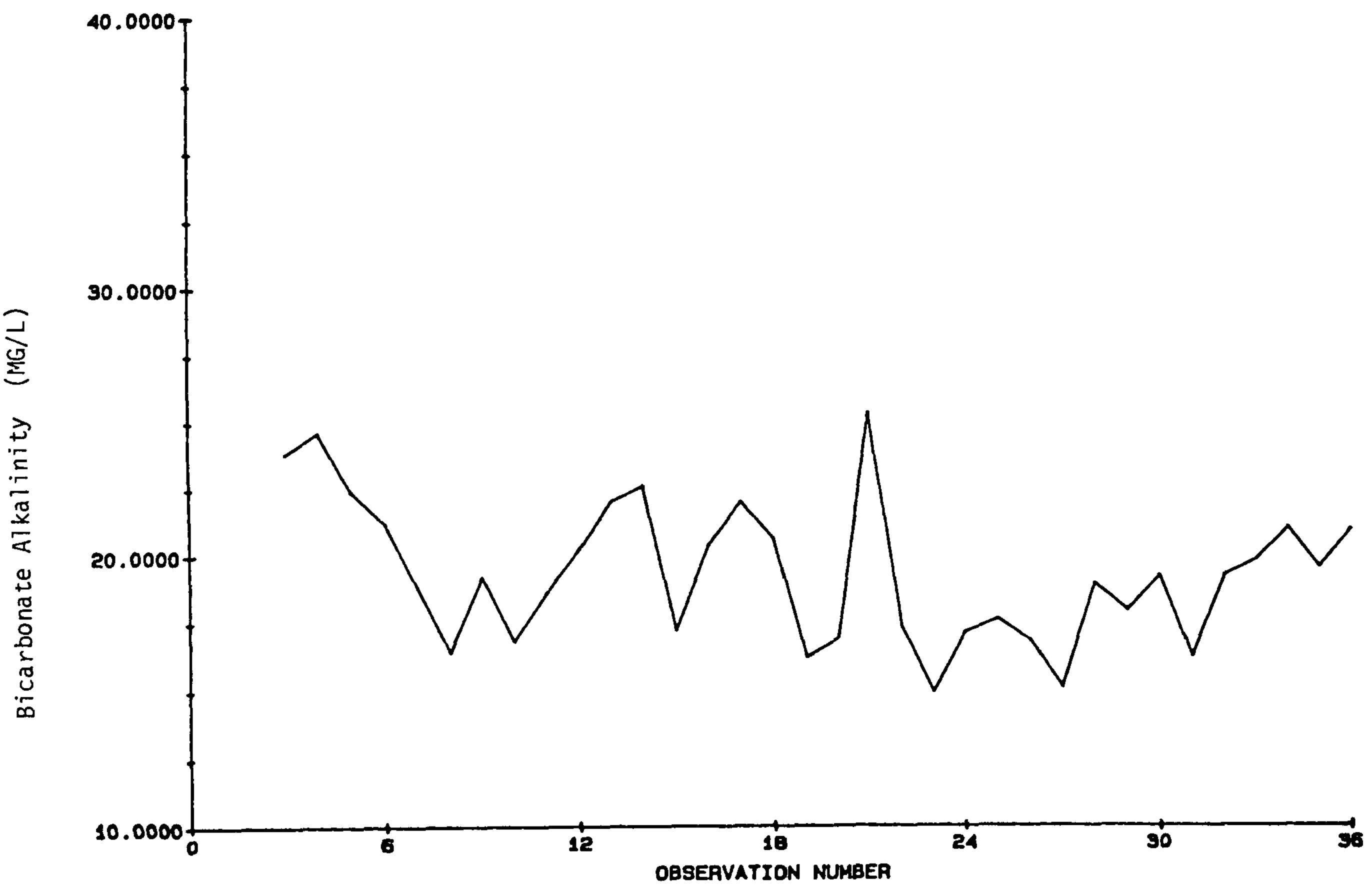


Figure 4-43. Quarterly time series of ANC data, in mg L^{-1} as bicarbonate, from Twin Lakes, Colorado, Station 4, beginning in January 1977.

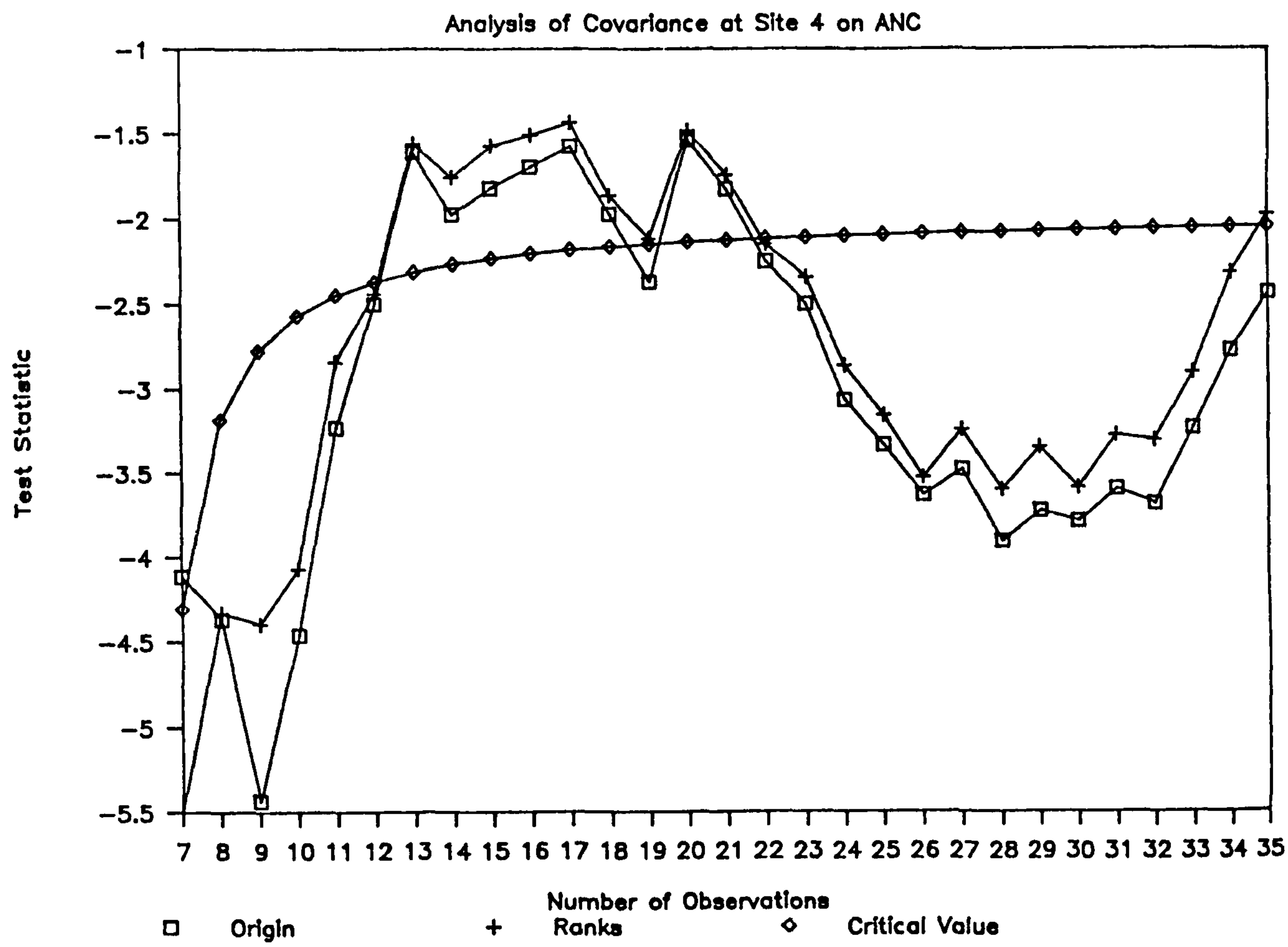


Figure 4-44. Results of ANOCOV on raw ANC and on ranks of ANC time series shown in Figure 4-43. Critical value of the test statistic is shown for each number of observations. The test is significant when the calculated statistic is more negative than the critical value.

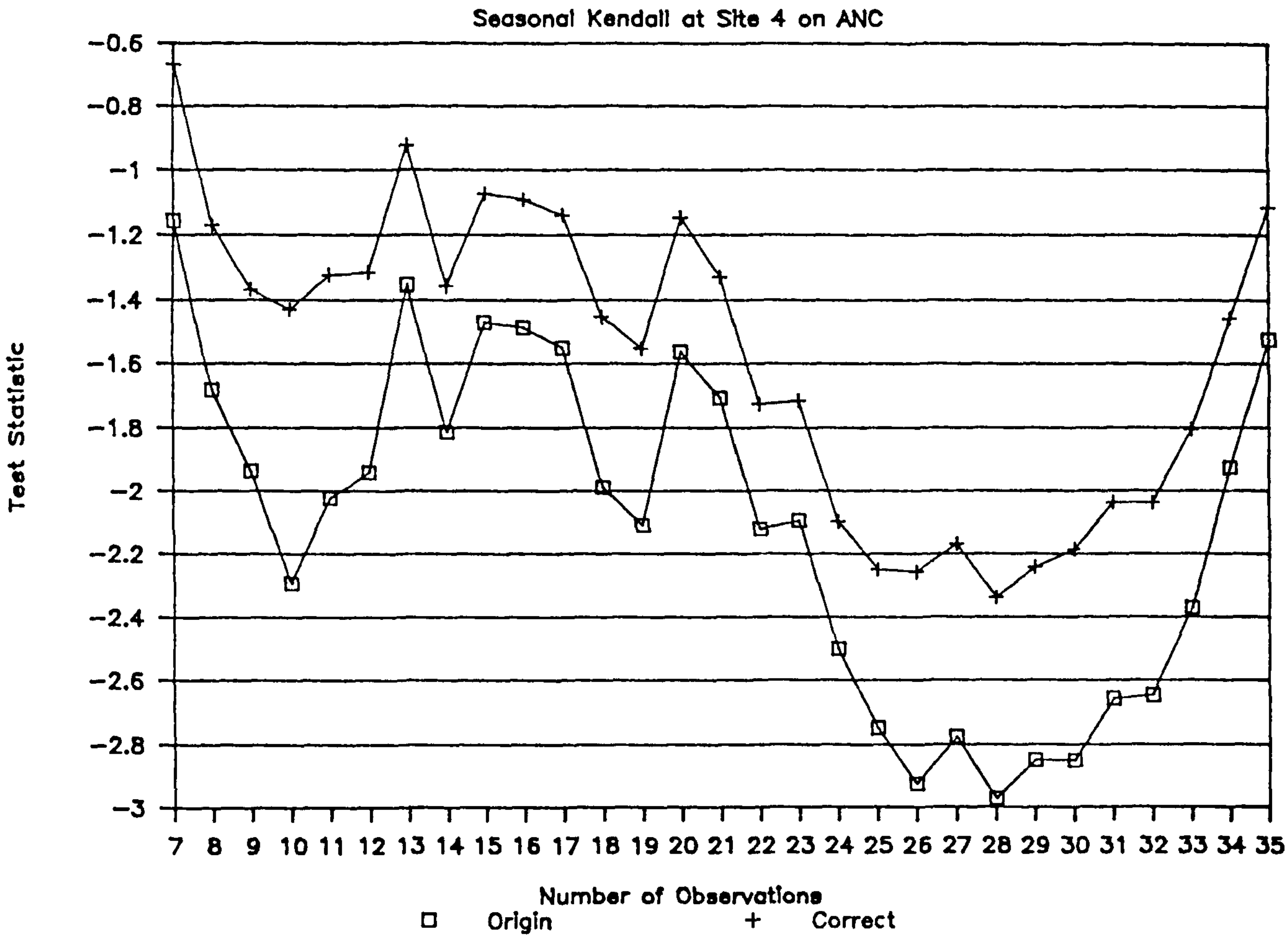


Figure 4-45. Results of seasonal Kendall (square symbols) and seasonal Kendall with correction for serial correlation (plus symbols) for raw ANC data shown in Figure 4-43.

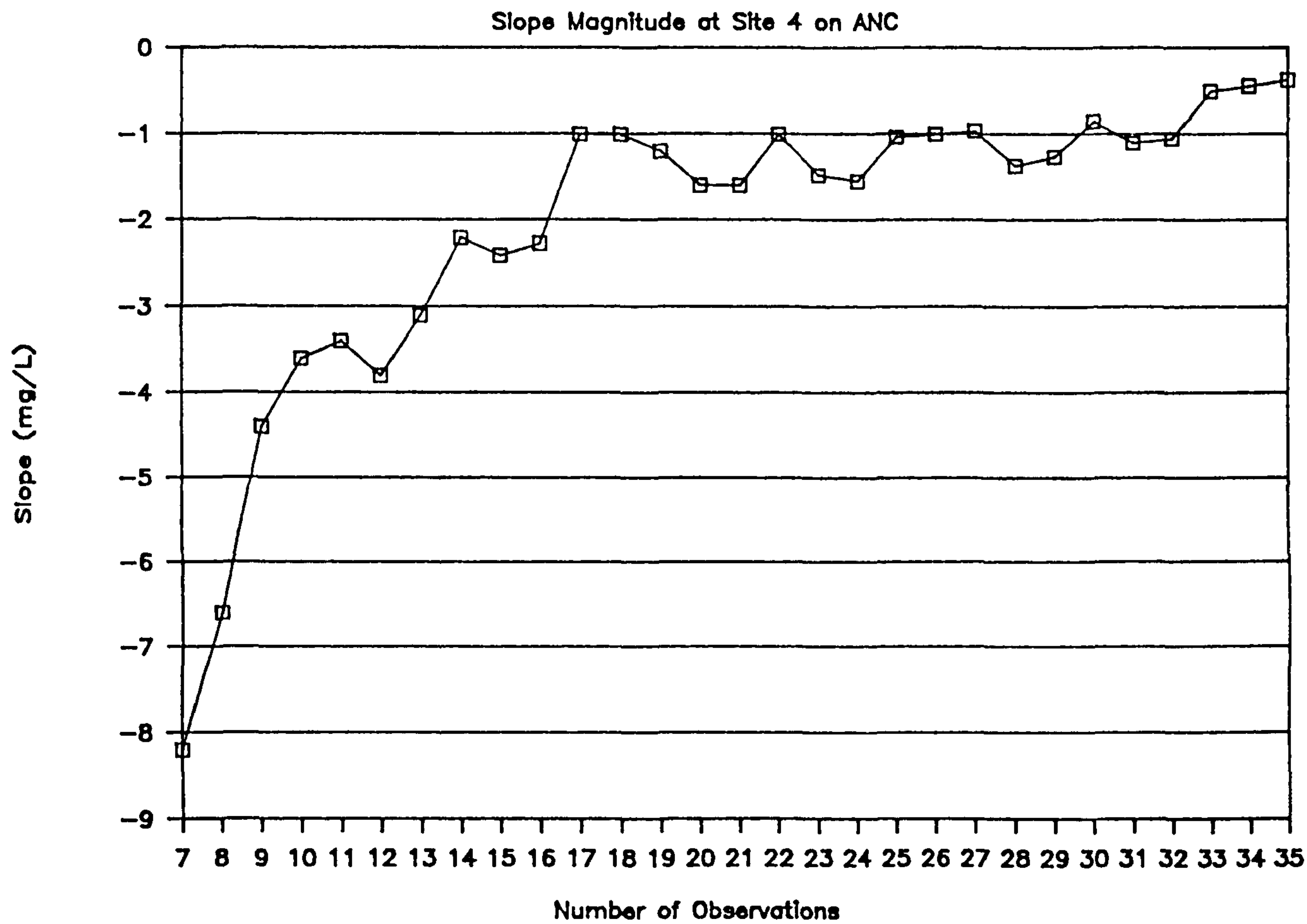


Figure 4-46. Least squares regression slope of the entire ANC series at Station 4 in Twin Lakes, Colorado, as a function of number of observations.

SECTION 5
SPECIALIZED PROCEDURES FOR EXPLANATION OF TRENDS

The trend testing procedures discussed thus far are designed for "quick-and-easy" analysis of TIME series for individual variables at single locations (or average values over multiple locations). They are broadly applicable and do not require local adjustment. Thus, they can be applied over the entire country for the entire suite of TIME water quality variables. The procedures are ideal screening or exploratory tools for routine data anlysis in national or regional routine monitoring programs--providing useful, comparable results quickly and efficiently.

However, because of their flexibility, the methods are not well suited for explaining the causes of trends. They can tell only whether apparent trends are likely to be the result of chance or of "real" change. Specialized techniques that consider interrelationships among multiple water quality variables and/or local watershed conditions are sure to be more powerful for detecting trends of a certain type (caused by acid rain, for example) and for explaining possible causes of trends that are indicated by exploratory analysis. Of course, strictly speaking, an observational study like TIME cannot establish "cause." It can only formulate explanations of causal mechanisms that are consistent with observations.

5.1 ADJUSTMENT FOR HYDROLOGIC FACTORS--STREAM FLOW AND PRECIPITATION

For streams, the effect of flow/concentration relationships should always be considered in trend monitoring. The simplest way to account for such relationships is to use an appropriate data transformation to obtain flow-adjusted concentrations. Trend tests may then be applied to both adjusted and nonadjusted data. Significant trends in nonadjusted data that do not appear in flow adjusted data are deemed to be the result of changes in flow.

Since there are many causes of flow/quality relationships, the functional form of flow adjustments is highly dependent on local factors (Hirsch et al., 1982). Local calibration, either from long-term records or short-term intensive studies, is necessary. Thus flow adjustments may not be possible, initially, at all TIME stream stations unless they correspond to USGS or other longer term monitoring locations. Once calibrated, flow adjustments become a part of routine data analysis, although periodic reevaluation and recalibration of flow/quality relationships are required.

Lakes, of course, do not exhibit the same sort of flow/quality relationship as streams. However, the same processes--dilution, washoff, etc.--affect lake quality. Thus, correction for precipitation (or inflow or lake level) is appropriate and analogous to flow correction in streams. The same requirements for local calibration over significant time periods apply.

5.2 WATER QUALITY INDICES

Observed values of multiple water quality variables (more than one constituent, time, or location) may be combined to provide a single number that effectively represents water quality relative to some particular standard, intended use, or external impact (Dinius, 1987). The arithmetic average of ANC over several lakes for a single quarter is such an index, as is the ratio of ANC to sulfate. Although any combination of water quality variables into a single one may be thought of as an index, the more common forms are linear combinations or ratios (or both) of two or more water quality constituents for one location at one time.

As single variables, water quality indices can be tested for trend using the SK and ANOCOV procedures. The nature of the index can provide considerable insight into the cause of any significant trend, since the ideal index would be highly sensitive to the changes in water quality in which we are interested--for example acid deposition effects--and very insensitive to other changes or variability.

The construction of effective water quality indices is difficult, requiring considerable water quality data and good understanding of the biological, chemical, physical, and hydrological factors determining water quality at a particular location. The more detailed and discriminatory an index, the more dependent it is on local factors; thus, the less transportable and broadly applicable it becomes.

5.3 MULTIVARIATE TESTS FOR TREND

Both the ANOCOV and SK tests can be viewed as multivariate procedures in that they consider water quality observations from different seasons simultaneously. For both tests, extensions are possible such that more than one variable or more than one location may be considered. An example of such a test is proposed by Dietz and Killeen (1981). Their test, based on Kendall-tau, considers the possibility that some variables might have upward trends while others trend downward. Hirsch and Slack (1984) suggest, though, that the Dietz and Killeen test would be applicable only for very long records (at least when used on a single variable as an alternative to SK).

ANOCOV is ideally suited for multivariate extensions. A vector of response variables can be considered, as in [Ca^{++}, ANC, $SO_4^{=}$] instead of a single variable. Other predictive variables can be added to the list of four that are used to indicate year and season. Possibilities for additional covariates include stream flow or lake level, quarterly precipitation, acid deposition, and additional water quality variables. In the general case, the covariates can be log linear transformations (perhaps including rank transformations) of observed values of predictive variables. However, comparatively little work has been done on multivariate trend detection and additional research is needed on both general and site specific levels.

5.4 WATER QUALITY/WATERSHED MODELS

At a more intensive level of study, it will be possible to obtain process descriptions and hydrologic/chemical/biological models of system behavior. Using such models, carefully calibrated for local geochemistry and other factors, it should be possible to identify specific and quantitative input-output relationships between such factors as acid deposition over a watershed and chemical response of receiving waters. Such relationships will be helpful in studying both long-term trends and episodic responses. (The latter short-term effects may not result in statistically significant trend.)

Only at this level is it possible to forecast water quality conditions and to examine "what if" scenarios that might be useful in developing management strategies. This level of data analysis, process modeling, is far from routine and is thus distinct from the earlier discussion. However, routinely collected data are useful for calibration and verification of watershed type models over a range of hydrologic conditions. Furthermore, background data sets are needed when models are moved from one watershed to another. Therefore, routine monitoring plays an important role, even at the level of intensive studies or research, in a monitoring program such as TIME that is designed to support water quality management on a broad geographical and long-term basis.

SECTION 6
DETAILS OF TREND TESTING AND MONTE CARLO METHODS

In an attempt to find a good method of trend detection in seasonal time series data, seven different tests were analyzed by means of simulation. Three of the tests are based on the Mann-Kendall test (Mann, 1945; Kendall, 1975), which utilizes the sign of the pairwise differences of the data. Two of the tests, the analysis of covariance and a modified t-test, use a linear model and normal theory. The final two tests are the application of the analysis of covariance and the modified t-test to the ranks of the data.

6.1 MANN-KENDALL TESTS

The first method of trend detection discussed in this section consists of applying the original Mann-Kendall test to deseasonalized data. That is, if an observation is made during season i, $i = 1(1)p$, where p is the number of seasons, then the mean of all observations made during season i is subtracted from this observation. The Mann-Kendall test is then applied to these differences.

The Mann-Kendall procedure tests the null hypothesis that the observations are randomly permuted against the alternative hypothesis of a monotone trend. Define

$$\mathrm{sign}(x) = \begin{array}{l} 1 \text{ if } x > 0 \\ 0 \text{ if } x = 0 \\ -1 \text{ if } x < 0 \end{array}$$

If we apply the Mann-Kendall test to the sequence $\{X_i: i = 1(1)n\}$, then under the null hypothesis, the test statistic

$$S = \Sigma \text{ sign } (X_j - X_i)$$

is normally distributed with a mean of zero and a variance,

$$\text{var } (S) = n(n-1)(2n + 5)/18.$$

The seasonal Kendall test automatically compensates for seasonality in the mean of the data. If our seasonal data is the sequence $\{Y_{ij}: i = 1(1)n, j = 1(1)p\}$, where n is the number of years and p is the number of seasons, then for each season, j, compute

$$S_j = \Sigma \text{ sign } (Y_{kj} - Y_{lj})$$
(Sum is for $k < l$)

The test statistic is the sum $S = \Sigma S_j$, which has a zero mean and a variance of

$$\text{var } (S) = \Sigma \text{ var}(S_j) + \sum_{j \neq k} \text{cov}(S_j, S_k).$$

Note that each S_j is the original Mann-Kendall test statistic computed from the j^{th} season's data.

We considered two versions of this seasonal Kendall test. The first (Hirsch et al., 1982) assumes that the covariance terms in the var(S) are negligible. Thus

$$\begin{aligned} \text{var}(S) &= \Sigma\, \text{var}(S_j) = \Sigma\, [n(n-1)(2n+5)/18] \\ &= p[n(n-1)(2n+5)/18] \end{aligned}$$

In the other version (Hirsch and Slack, 1984), the covariances are estimated as

$$\text{cov}(S_j,S_k) = K_{jk}/3 + (n^3 - n)r_{jk}/9$$

where

$$K_{jk} = \sum_{l<m} \text{sign}[(X_{lj} - X_{mj})(X_{lk} - X_{mk})]$$

$$r_{jk} = \frac{3}{n^3 - n} \Sigma\, \text{sign}[(X_{lj} - X_{mj})(X_{lk} - X_{qk})]$$

(summed over l, m, and q).

Adjustments to this variance are given in Hirsch and Slack (1984) to compensate for missing values.

6.2 LINEAR MODEL TESTS

Two of our tests, the analysis of covariance and the modified t, are based on the underlying linear model

$$Y_{ij} = \beta_0 + \beta_1[(i-1)p+j] = \mu_j + \epsilon_{ij}$$

$$(\text{where } i = 1(1)n \text{ and } j = 1(1)p)$$

and normal theory. The seasonality of the quarterly means is modeled by the μ_i, and the ϵ_{ij} are assumed to be independently distributed normal with a zero mean and variance σ_j^2.

The analysis of covariance consists of a multiple regression of a dependent variable Y_{ij} on p independent variables, $t = [(i-1)p+j]$ and $\{u_{kij} \mid k = 1(1)p-1\}$ where

$$u_{ij} = \begin{cases} 1 \text{ if } j = k \\ -1 \text{ if } j = p \\ 0 \text{ otherwise} \end{cases}$$

In the regression equation, the coefficient of t, β_1, represents a linear trend in Y, and the coefficients of u_{kij}, say M_k, compensate for any seasonality in the quarterly means of Y. (Only three indicator variables are needed for four means, since $M_1 + ... + M_p = 0$ by assumption.) Hence, by usual linear methods, we may estimate β_1 and test for a linear trend while automatically adjusting for seasonality in the means. This type of linear regression of a dependent variable on a continuous independent variable and on a set of indicator variables is typically called analysis of covariance and is discussed fully in Neter and Wasserman (1974).

Note that, as in all standard linear regression, it is assumed the variances of all of the observations are equal. Clearly, this is not the case. However, it is of interest to see how this procedure performs when this assumption is not valid. We remove this assumption with the modified t-test, which is discussed in the next section.

6.3 MODIFIED T-TEST

As mentioned in subsection 6.2, our water quality data generally do not satisfy the homogenity of variance assumption of the analysis of covariance. In this section, we remove this assumption with the modified t-test.

The analysis of covariance procedure implicitly assumes that the linear trend, if it exists, remains constant over the p seasons. Suppose this assumption is maintained, and a separate simple regression of Y_{ij} versus $t = [p(i-1) + j]$ is computed for each $j = 1(1)p$. The sum of the p resulting estimates of β_1 (denoted by $\{b_j \mid j = 1(1)p\}$) may now be utilized for a test of $\beta_1 = 0$, which no longer requires the assumption of equal seasonal variances.

This test incorporates Satterthwaite's approximation of the distribution of a linear combination of independent χ^2 (chi-squared) random variables (Satterthwaite, 1946). Essentially, this approximation assumes that if $d_i Z_i/c_i \sim x^2$ (d_i and c_i are constants and Z_i is a random variable), with degrees of freedom d_i for $i = 1,\ldots,m$, then the sum, $W = \Sigma\, c_i Z_i/d_i$ is distributed as a scaled χ^2 (i.e., for constants c and d, dW/c is distributed χ^2 with degrees of freedom d). The constants c and d may be found by merely equating the first and second moments.

In order to derive this test, some definitions are needed. Define

$$\bar{t}_j = \frac{\Sigma\,(j + p(i-1))}{n} = \frac{(n - 1)p + 2j}{2} \quad \text{(summing over i)}$$

and

$$S_{t_j} = \Sigma\,(j + p(i-1) - \bar{t}_j)^2 = \frac{(n^3 - n)p^2}{12}$$

(summing over i)

Let MSE(j) be the mean squared error arising from regressing the observations belonging to season j on t - [p(i-1)+j]. Since MSE(j) can be used to adequately estimate the variance σ_j^2, the variance of b_j,

$$V(b_j) = \sigma_j^2/s_{t_j}\,,$$

can be estimated as

$$s_j^2 = \mathrm{MSE}(j)/s_{t_j}\,.$$

Since $(n - 2)\,\mathrm{MSE}(j)/\sigma_j^2 \sim \chi^2$ (degrees of freedom = n - 2), it is known that

$$E(\Sigma\, s_i^2) = \Sigma\, \sigma_j^2/s_{t_j}$$

and

$$V(\Sigma s_j^2) = \frac{2(\Sigma \sigma_j^4/s_{t_j}^2)}{n - 2}$$

Now, if we claim that $W = \Sigma s_j^2$ has a scaled χ^2 distribution with degrees of freedom d and a scale parameter of c, then we can solve for c and d by equating the first two moments. That is, let

$$E(\Sigma s_j^2) = c \text{ and}$$

$$V(\Sigma s_j^2) = 2c^2/d$$

then

$$d = \frac{(\Sigma \sigma_j^2/s_{t_j})^2}{\frac{2(\Sigma \sigma_j^4/s_{t_j}^2)}{n - 2}}$$

Although the σ_j^2 are not known, they can then be estimated by MSE(j). Therefore, we can estimate the degrees of freedom as

$$d^* = \frac{(\Sigma s_j)^2}{(\Sigma s_1^2)/(n-2)}$$

Since the sum Σb_i is distributed normal with a mean $\Sigma\beta_i$ and variance c,

$$T = \frac{(\Sigma b_i)/\sqrt{c}}{[(\Sigma s_1^2)/c]^{\frac{1}{2}}}$$

$$= \frac{\Sigma b_j}{(\Sigma s_j^2)^{\frac{1}{2}}}$$

is approximately distributed t with df = d*. Thus, we can use T as our test statistic, and test it against the Student's t distribution with d* degrees of freedom.

6.4 RANK TRANSFORMATIONS

Conover (1980) suggests using ranks instead of the raw data as a nonparametric extension of multiple regression techniques. Hence, two additional tests involve using the analysis of covariance and the modified "t" on the ranks of data, rather than on the raw data.

6.5 MONTE CARLO SIMULATIONS

In order to compare the seven different tests, we performed an extensive simulation study. Simulated data records consisting of 5, 15, and 25 years (n = 5, 15, 25) of quarterly (p = 4) data were generated with a variety of different trend magnitudes and seasonality in the means and the standard deviations.

The data were generated with models of the form

$$y_{ij} = m_j + b\,[4(i-1)+j] + e_{ij}$$

where, as before, i indexes the year and j indexes the season. The parameters m_j, $j = 1,...,4$, introduce seasonality. The number b gives a trend to the data (for $b \neq 0$), and the e_{ij} is a simulated random error.

For each model, the seasonality parameters, m_j, were constrained to sum to four, and each m_j took one of two possible values denoted by "high" or "low." Different ratios of "high" to "low", denoted by r_m, as well as two different patterns of seasonality, (low, high, low, low) and (high, low, high, low), were considered. Therefore, the seasonality in the means is uniquely specified by the pattern of seasonality and r_m.

The errors, e_{ij}, were generated for the normal and the lognormal distributions. In the case of the normal distribution, both uncorrelated and correlated errors were produced. Furthermore, seasonality in the standard deviations of these errors was introduced. This seasonality followed the same high/low pattern as for the means, with the ratio of high to low set to r_s. However, unlike the means, σ_j was set to 1.0 for seasons with "low" standard deviations and to r_s for seasons with "high" standard deviations.

For each set of parameters (the term "parameters" includes the number of years and the pattern of seasonality, as well as r_s, r_m, and b), 500 data records were created. All seven tests were applied to each record with a theoretical significance level of 0.05, and the total number of rejections for each test was recorded. A stepwise logistic regression procedure was used to determine which of the parameters significantly (at the 0.05 level) affected the simulated power. In all cases examined, all parameters had a significant effect, except for r_m, the ratio of season means.

The results of the simulations are presented in terms of simulated power. In Appendix B, Tables B-1 through B-6, results are presented according to the parameters that were found to be significant in the stepwise regression. For each combination of parameters, the number of rejections are summed over the values of r_m. The tabulated powers are this sum divided by the product of the number of values that r_m assumes and 500. Tables 6-1, 6-2, 6-3, and 6-4 summarize the combined results, according to length of record and trend magnitude only.

We attempted to use logistic regression techniques to model these powers as functions of the applied test procedure, as well as of the significant parameters. We hoped that a model could be established that would adequately explain the effects of the various parameters on powers of the different tests. Unfortunately, our available computer resources restricted our fitted model to second order or less, which was too crude for this application. Consequently, we are left to compare the tabulated results directly.

TABLE 6-1. SIMULATED POWERS FOR NORMAL ERRORS AFTER AVERAGING OVER RATIO OF STANDARD DEVIATIONS, RATIO OF MEANS, AND PATTERNS OF SEASONALITY

Years	Slope	Anal. of covar.	Mod. t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Mod. t on ranks
	.000	.0440	.0463	.0598	.0067	.0338	.0483	.0433
	.002	.0482	.0488	.0651	.0065	.0370	.0548	.0465
	.005	.0456	.0452	.0598	.0068	.0336	.0517	.0440
5	.020	.0612	.0562	.0774	.0097	.0447	.0675	.0560
	.050	.1418	.1216	.1723	.0175	.1108	.1527	.1281
	.200	.7642	.6956	.8486	.3191	.8276	.8259	.7816
	.500	.9815	.9629	.9930	.9276	.9949	.9881	.9838
	.000	.0518	.0506	.0578	.0432	.0475	.0534	.0523
	.002	.0520	.0528	.0623	.0482	.0513	.0554	.0545
	.005	.0705	.0697	.0807	.0681	.0722	.0758	.0753
15	.020	.4338	.4222	.5118	.4664	.5079	.4977	.4915
	.050	.8725	.8607	.9608	.9795	.9864	.9550	.9573
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.000	.0495	.0497	.0512	.0445	.0452	.0486	.0495
	.002	.0709	.0703	.0788	.0702	.0749	.0744	.0739
	.005	.1793	.1773	.2056	.1938	.2077	.2006	.1990
25	.020	.8224	.8158	.9307	.9691	.9741	.9271	.9278
	.050	.9978	.9977	1.0000	1.0000	1.0000	.9999	1.0000
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE 6-2. SIMULATED POWERS FOR LOGNORMAL ERRORS AFTER AVERAGING OVER RATIO OF STANDARD DEVIATIONS, RATIO OF MEANS, AND PATTERNS OF SEASONALITY

Years	Slope	Anal. of covar.	Mod. t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Mod. t ranks
	.000	.0388	.0369	.0504	.0058	.0362	.0509	.0438
	.002	.0426	.0398	.0561	.0096	.0383	.0540	.0468
	.005	.0405	.0383	.0581	.0103	.0425	.0615	.0533
5	.020	.0738	.0616	.1248	.0214	.1148	.1383	.1174
	.050	.2523	.2004	.3985	.1033	.4234	.4403	.3878
	.200	.8278	.7613	.9440	.7902	.9688	.9474	.9270
	.500	.9764	.9560	.9973	.9833	.9993	.9988	.9984
	.000	.0448	.0442	.0473	.0448	.0490	.0502	.0499
	.002	.0508	.0512	.0710	.0738	.0842	.0829	.0813
	.005	.0894	.0851	.1961	.2312	.2591	.2313	.2294
15	.020	.5368	.5212	.8708	.9498	.9615	.8842	.8843
	.050	.8957	.8879	.9972	1.0000	1.0000	.9975	.9983
	.200	.9988	.9987	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	.9999	.9999	1.0000	1.0000	1.0000	1.0000	1.0000
	.000	.0460	.0445	.0471	.0492	.0537	.0518	.0516
	.002	.0724	.0712	.1582	.2090	.2218	.1870	.1852
	.005	.2331	.2275	.6072	.7505	.7772	.6541	.6537
25	.020	.8531	.8459	.9960	1.0000	1.0000	.9968	.9973
	.050	.9908	.9899	1.0000	1.0000	1.0000	1.0000	1.0000
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE 6-3. SIMULATED POWERS FOR NORMAL ERRORS WITH ρ = 0.2 AFTER AVERAGING OVER RATIO OF STANDARD DEVIATIONS, RATIO OF MEANS, AND PATTERNS OF SEASONALITY

Years	Slope	Anal. of covar.	Mod. t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Mod. t ranks
	.000	.1393	.1155	.1722	.0130	.1230	.1617	.1302
	.002	.1402	.1140	.1700	.0107	.1212	.1587	.1358
	.005	.1375	.1177	.1733	.0108	.1202	.1582	.1308
5	.020	.1507	.1240	.1877	.0128	.1317	.1662	.1385
	.050	.2317	.1915	.2735	.0248	.2073	.2560	.2187
	.200	.7125	.6402	.8008	.3178	.8023	.7858	.7325
	.500	.9598	.9175	.9837	.8803	.9882	.9757	.9603
	.000	.1590	.1508	.1813	.0743	.1657	.1732	.1720
	.002	.1663	.1592	.1922	.0792	.1755	.1842	.1808
	.005	.1813	.1735	.2040	.0840	.1900	.1978	.1920
15	.020	.4478	.4383	.5288	.3480	.5385	.5215	.5143
	.050	.7850	.7682	.9118	.9043	.9553	.9050	.9052
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.000	.1538	.1495	.1765	.0730	.1760	.1732	.1692
	.002	.1760	.1735	.2020	.0903	.2025	.1972	.1932
	.005	.2652	.2597	.3048	.1683	.3068	.2995	.2955
25	.020	.7412	.7312	.8778	.8630	.9352	.8767	.8750
	.050	.9833	.9828	.9987	1.0000	1.0000	.9982	.9988
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE 6-4. SIMULATED POWERS FOR NORMAL ERRORS WITH ρ = 0.4 AFTER AVERAGING OVER RATIO OF STANDARD DEVIATIONS, RATIO OF MEANS, AND PATTERNS OF SEASONALITY

Years	Slope	Anal. of covar.	Mod. t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Mod. t ranks
	.000	.1393	.1155	.1722	.0130	.1230	.1617	.1302
	.002	.1402	.1140	.1700	.0107	.1212	.1587	.1358
	.005	.1375	.1177	.1733	.0108	.1202	.1582	.1308
5	.020	.1507	.1240	.1877	.0128	.1317	.1662	.1385
	.050	.2317	.1915	.2735	.0248	.2073	.2560	.2187
	.200	.7125	.6402	.8008	.3178	.8023	.7858	.7325
	.500	.9598	.9175	.9837	.8803	.9882	.9757	.9603
	.000	.1590	.1508	.1813	.0743	.1657	.1732	.1710
	.002	.1663	.1592	.1922	.0792	.1755	.1842	.1808
	.005	.1813	.1735	.2040	.0840	.1900	.1978	.1920
15	.020	.4478	.4383	.5288	.3480	.5385	.5215	.5143
	.050	.7850	.7682	.9118	.9043	.9553	.9050	.9052
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.000	.1538	.1495	.1765	.0730	.1760	.1732	.1692
	.002	.1760	.1735	.2020	.0903	.2025	.1972	.1932
	.005	.2652	.2597	.3048	.1683	.3068	.2995	.2955
25	.020	.7412	.7312	.8778	.8630	.9352	.8767	.8750
	.050	.9833	.9828	.9987	1.0000	1.0000	.9982	.9988
	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

6.5.1 Normal Uncorrelated Errors

In the case of normal errors with no correlation, we considered

$$b = 0.0, 0.002, 0.005, 0.02, 0.05, 0.2, 0.5$$
$$r_m = 1.0, 1.5, 2.0$$
$$r_s = 1.0, 1.5, 3.0, 5.0$$

Observations from independently distributed standard normal random variables were generated by the IMSL subroutine, GGNML. These observations are denoted by

$$\{z_{ij} \mid i=1(1)n, j=1(1)4\}$$

where, as with the y_{ij}, i indexes the year and j indexes the season. The errors, e_{ij} were created as

$$e_{ij} = z_{ij}\sigma_j$$

As we can see from Tables 6-1, B-1, and B-2, the best tests appear to be the analysis of covariance on ranks, the modified "t", and the seasonal Kendall test without correction for correlation. The other procedures are considered to perform less well than these three tests because either their powers were less or their simulated critical value (power when $\beta_1 = 0$) was greater than 0.05.

In general, these three tests gave similar performances. However, for short records (5 years), the analysis of covariance on ranks was the best test, except when $r_s = 5.0$. With longer records, the only discrimination between the performances of these tests occurs for $r_s =$ 3.0 and 5.0. In these cases, the seasonal Kendall test without correction for correlation has the highest power.

As expected, for all of the tests we see a general decrease in power with an increase in seasonality. Not only does the power drop with an increasing r_s, but the powers are less for the pattern of seasonality

{high, low, high, low}

than for the pattern

{low, high, low, low}

This also agrees with intuition, since the second pattern has higher "overall" variance.

6.5.2 Lognormal Errors

The seven tests were also compared when the errors were lognormally distributed and the parameters had the same specifications as for the normal errors. The lognormal errors were created by first generating the standard normal observations z_{ij} and then letting

$$d_{ij} = [\exp(z_{ij}) - \exp(1/2)]/[\exp(2) - \exp(1)],$$

which are distributed lognormal with a zero mean and a variance of one. Then let

$$e_{ij} = d_{ij}\sigma_j,$$

which will be lognormally distributed with a zero expected value and variances corresponding to the definition of r_s and the patterns of standard deviations.

From Tables 6-2, B-3, and B-4, we can see that the best tests for lognormal errors were the analysis of covariance on ranks, the modified "t" on ranks, and the seasonal Kendall test without correction for correlation. The analysis of covariance on ranks has the highest powers for short records, except for $r_s = 5.0$. In this case, the seasonal Kendall test without correction for correlation performed better than the other methods. For longer records, the seasonal Kendall test without correction for correlation performed better than the other two methods.

As with normal errors, we see an overall decrease in power with an increase in seasonality. Again, this increase in seasonality is given by both an increase in r_s and a change in the pattern of standard deviations from

{low, high, low, low}

to

{high, low, high, low}

6.5.3 Normal Errors with Positive Correlation

In this case, we introduce a positive correlation between e_{ij} and the previously "observed" error, $e_{ij,-1}$ ($e_{ij,-1} = e_{i^*j^*}$, where

$$(i^*, j^*) = \begin{matrix} (i, j - 1) \text{ if } j > 1). \\ (i - 1, p) \text{ if } j = 1 \end{matrix}$$

First, a sequence of standard normal observations, z_t ($t = 1(1)np$), was generated with the IMSL subroutine, GGNML. From the z_t, an AR(1) process, d_t, is generated with a lag-one correlation, $\rho = 0.2, 0.4$. This is accomplished by letting

$$d_t = \sqrt{(1 - \rho^2)}\, z_t + \rho d_{t-1}$$

Thus, the sequence of d_t's has a lag-one correlation, ρ, and a stationary variance of unity. Since d_t depends on d_{t-1}, d_1 is set equal to a standard normal observation. Then the process is "warmed up" by generating 500 preliminary observations.

After establishing the AR(1) process, e_{ij} is generated as

$$e_{ij} = \sigma_j\, d_{4(i-1)+j}.$$

This gives a positively correlated sequence with seasonal variances. Note, however, that the lag-one correlation is no longer ρ, and it is now dependent on j. Specifically,

$$\frac{\rho}{\sigma_j\, \sigma_{j-1}} \quad \text{if } j \geq 2$$

$$\mathrm{corr}(e_{ij}, e_{ij,-1}) = \frac{\rho}{\sigma_1 \sigma_4} \qquad \text{if } j = 1$$

Simulations for this error structure were run with

r_m = 1.0, 1.5, 2.0
r_s = 1, 5
b = 0, 0.002, 0.005, 0.02, 0.05, 0.2, 0.5

Tables 6-3, B-5, and B-6 show that none of the seven tests performed very well. With the exception of the seasonal Kendall test with correction for correlation, all of the test procedures had excessive significance levels for both levels of r_s and ρ, for all three record lengths. On the other hand, the seasonal Kendall test with correction for correlation had very small significance levels for five years of data. (For five years of data and $\rho = 0.2$, the significance level for the seasonal Kendall test without correction for correlation is not much larger than 0.05. Hence, we might consider using this test for short records and low correlation.) For 15 and 25 years of data, the significance levels of the corrected SK test were acceptable for ρ = 0.2. However, for $\rho = 0.4$, the significance levels were large, but not nearly as large as those for the other tests. Therefore, it appears that the best procedure for large data records and small correlations is the Seasonal Kendall test with correction for correlations.

6.5.4 Summary

For uncorrelated errors, the best methods of detecting trends in time series are the analysis of covariance on ranks and the seasonal Kendall without correction for correlation. From the tables of simulated powers, we can see that for the most part, the difference in performance between these two methods is not large. Hence, both of these two tests appear to be appropriate for detection of trends in seasonal time series with uncorrelated errors. However, if a choice must be made between these two methods, the seasonal Kendall is recommended, especially for long data records.

For correlated data, none of the tests appears to be very good. However, the seasonal Kendall test with correction for correlation appears to be sufficient for large data records with small correlations.

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ABBREVIATIONS AND ACRONYMS

ANC	--	Acid neutralizing capacity
ANOCOV	--	Analysis of covariance
Ca	--	Calcium
LTM	--	Long-term Monitoring
NLS	--	National Lake Survey
NLS-1A	--	National Lake Survey subregion 1A - Adirondacks
NLS-1B	--	National Lake Survey subregion 1B - Poconos/Catskills
NLS-1C	--	National Lake Survey subregion 1C - Central New England
NLS-1D	--	National Lake Survey subregion 1D - Southern new England
NLS-1E	--	National Lake Survey subregion 1E - Maine
NRC	--	National Research Council
OLS	--	Ordinary least squares
SK	--	Seasonal Kendall
SO_4	--	sulfate
TIME	--	Temporally Integrated Monitoring of Ecosystems

APPENDIX A
TIME GOALS AND OBJECTIVES

(Reprinted from "The Concept of Time" Report)

To provide a regional-scale assessment of the effects of acidic deposition on aquatic ecosystems, a long-term monitoring program needs to incorporate representative site selection, measurement of biologically relevant chemical variables, standardized analytical methods and quality assurance protocols, and a sampling scheme that permits long-term changes in chemical response to be differentiated from episodic changes and short-term daily, monthly, or annual periodicities. The monitoring program must be predicted on a clear set of goals and objectives.

GOALS

The TIME Project has as its goals to:

- Estimate the regional proportion and subpopulation physiochemical characteristics of lakes and streams that exhibit early and ongoing trends of surface water acidification or recovery.

- Compare patterns and trends in observed surface water chemistry to forecasts made using empirical or process-oriented procedures.

- Determine the relationships between patterns and trends in atmospheric deposition and trends in surface water chemistry for defined subpopulations of aquatic resources in areas particularly susceptible to acidification or recovery.

OBJECTIVES

In order to achieve these goals, the TIME project has the following objectives:

- Provide an early and ongoing indication of regional trends in surface water acidification or recovery, using the most appropriate techniques to detect such trends.

- Quantify, with known certainty, for defined subpopulations of lakes and streams:

    - The rate at which changes in relevant chemistry are occurring.
    - The subpopulation characteristics of the affected lakes and/or streams.
    - The regional or subregional extent of these systems.

- Compare trends in local and regional atmospheric deposition with regional trends in surface water chemistry.

APPENDIX B
RESULTS OF SIMULATIONS

This appendix presents the results of simulations in terms of simulated power. Tables B-1 through B-6 show the results according to the parameters that were found to be significant in the stepwise regression. For each combination of parameters, the number of rejections are summed over the values of r_m. The tabulated powers are this sum divided by the product of the number of values that r_m assumes and 500.

TABLE B-1a. Powers of trend detection for normal errors with five years of data and with a seasonal pattern of variances (low, high, low, low)

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0513	.0453	.0707	.0053	.0380	.0547	.0447
1.5	.000	.0447	.0407	.0627	.0073	.0360	.0467	.0433
3.0	.000	.0440	.0527	.0580	.0087	.0313	.0507	.0453
5.0	.000	.0340	.0640	.0533	.0053	.0300	.0473	.0393
1.0	.002	.0560	.0467	.0673	.0053	.0380	.0600	.0493
1.5	.002	.0480	.0427	.0593	.0053	.0320	.0480	.0433
3.0	.002	.0487	.0600	.0713	.0067	.0413	.0580	.0480
5.0	.002	.0367	.0593	.0660	.0087	.0373	.0513	.0453
1.0	.005	.0560	.0453	.0707	.0073	.0433	.0620	.0513
1.5	.005	.0447	.0433	.0493	.0033	.0260	.0427	.0307
3.0	.005	.0380	.0460	.0567	.0067	.0287	.0413	.0367
5.0	.005	.0340	.0633	.0593	.0093	.0367	.0520	.0507
1.0	.020	.0727	.0613	.0880	.0093	.0447	.0740	.0633
1.5	.020	.0787	.0593	.0873	.0087	.0473	.0747	.0620
3.0	.020	.0533	.0567	.0767	.0120	.0440	.0613	.0453
5.0	.020	.0387	.0673	.0673	.0107	.0493	.0660	.0573
1.0	.050	.2240	.1900	.2493	.0180	.1380	.2100	.1793
1.5	.050	.1827	.1567	.2033	.0200	.1327	.1907	.1620
3.0	.050	.1147	.1040	.1507	.0147	.1093	.1367	.1167
5.0	.050	.0813	.0747	.1460	.0200	.1067	.1313	.1020
1.0	.200	.9967	.9967	.9960	.4673	.9713	.9927	.9887
1.5	.200	.9847	.9647	.9867	.3907	.9453	.9787	.9707
3.0	.200	.7773	.6467	.8880	.3307	.8487	.8647	.8087
5.0	.200	.5133	.3400	.7893	.2760	.8067	.7340	.6393
1.0	.500	1.0000	1.0000	1.0000	.9980	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	.9980	1.0000	1.0000	1.0000
3.0	.500	1.0000	.9987	1.0000	.9720	1.0000	1.0000	1.0000
5.0	.500	.9753	.9193	1.0000	.9527	1.0000	.9927	.9880

TABLE B-1b. Powers of trend detection for normal errors with fifteen years of data and with a seasonal pattern of variances (low, high, low, low)

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0540	.0547	.0587	.0473	.0547	.0580	.0573
1.5	.000	.0527	.0500	.0560	.0413	.0420	.0533	.0513
3.0	.000	.0480	.0440	.0533	.0407	.0453	.0500	.0480
5.0	.000	.0460	.0467	.0600	.0433	.0480	.0527	.0520
1.0	.002	.0533	.0547	.0680	.0473	.0560	.0620	.0587
1.5	.002	.0587	.0567	.0633	.0533	.0553	.0573	.0587
3.0	.002	.0527	.0500	.0593	.0480	.0487	.0513	.0507
5.0	.002	.0453	.0493	.0593	.0460	.0467	.0533	.0533
1.0	.005	.0853	.0840	.0827	.0700	.0740	.0853	.0840
1.5	.005	.0813	.0800	.0913	.0667	.0793	.0860	.0853
3.0	.005	.0753	.0740	.0873	.0693	.0733	.0707	.0727
5.0	.005	.0580	.0600	.0853	.0793	.0800	.0787	.0753
1.0	.020	.7300	.7280	.7307	.6213	.6693	.7200	.7153
1.5	.020	.6307	.6273	.6427	.5327	.5813	.6307	.6267
3.0	.020	.3360	.3107	.5060	.4740	.5227	.4920	.4833
5.0	.020	.1853	.1620	.4140	.4400	.4773	.4000	.3920
1.0	.050	1.0000	1.0000	1.0000	.9987	1.0000	1.0000	1.0000
1.5	.050	1.0000	1.0000	1.0000	.9993	1.0000	1.0000	1.0000
3.0	.050	.9593	.9553	.9960	.9953	.9973	.9933	.9960
5.0	.050	.7173	.6593	.9860	.9933	.9973	.9773	.9840
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-1c. Powers of trend detection for normal errors with twenty-five years of data and with a seasonal pattern of variances {low, high, low, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0513	.0513	.0573	.0513	.0520	.0547	.0547
1.5	.000	.0520	.0507	.0520	.0493	.0507	.0527	.0533
3.0	.000	.0373	.0367	.0400	.0340	.0327	.0387	.0400
5.0	.000	.0553	.0573	.0520	.0433	.0453	.0493	.0500
1.0	.002	.0887	.0860	.0933	.0787	.0873	.0840	.0820
1.5	.002	.0747	.0753	.0853	.0727	.0793	.0767	.0760
3.0	.002	.0627	.0627	.0720	.0700	.0760	.0720	.0713
5.0	.002	.0580	.0580	.0773	.0720	.0680	.0713	.0700
1.0	.005	.2940	.2947	.2993	.2513	.2693	.2853	.2847
1.5	.005	.2407	.2380	.2440	.2040	.2313	.2353	.2353
3.0	.005	.1473	.1373	.1867	.1867	.2047	.1900	.1867
5.0	.005	.0993	.0973	.1807	.1947	.2027	.1767	.1740
1.0	.020	1.0000	1.0000	1.0000	.9993	1.0000	1.0000	1.0000
1.5	.020	1.0000	1.0000	.9993	.9980	.9993	.9993	.9993
3.0	.020	.9120	.9060	.9840	.9913	.9953	.9820	.9853
5.0	.020	.5813	.5533	.9533	.9807	.9833	.9527	.9540
1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.050	.9993	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-2a. Powers of trend detection for normal errors with five years of data and with a seasonal pattern of variances {high, low, high, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0513	.0453	.0707	.0053	.0380	.0520	.0473
1.5	.000	.0447	.0373	.0520	.0073	.0360	.0433	.0393
3.0	.000	.0367	.0367	.0527	.0087	.0313	.0447	.0400
5.0	.000	.0453	.0487	.0580	.0053	.0300	.0473	.0473
1.0	.002	.0560	.0467	.0673	.0053	.0380	.0573	.0487
1.5	.002	.0467	.0433	.0580	.0053	.0320	.0447	.0407
3.0	.002	.0507	.0447	.0680	.0067	.0407	.0607	.0493
5.0	.002	.0427	.0473	.0633	.0087	.0367	.0580	.0473
1.0	.005	.0560	.0453	.0707	.0073	.0433	.0547	.0500
1.5	.005	.0473	.0433	.0540	.0033	.0260	.0493	.0400
3.0	.005	.0427	.0373	.0593	.0067	.0287	.0527	.0420
5.0	.005	.0460	.0373	.0587	.0100	.0360	.0587	.0507
1.0	.020	.0727	.0613	.0880	.0093	.0447	.0747	.0660
1.5	.020	.0713	.0480	.0840	.0113	.0447	.0713	.0567
3.0	.020	.0540	.0507	.0687	.0093	.0373	.0580	.0473
5.0	.020	.0480	.0447	.0593	.0067	.0453	.0600	.0500
1.0	.050	.2240	.1900	.2493	.0180	.1380	.2067	.1740
1.5	.050	.1600	.1260	.1733	.0187	.1093	.1540	.1367
3.0	.050	.0827	.0753	.1160	.0187	.0820	.1087	.0820
5.0	.050	.0647	.0560	.0900	.0120	.0707	.0833	.0720
1.0	.200	.9967	.9967	.9960	.4673	.9713	.9933	.9900
1.5	.200	.9627	.9360	.9647	.3153	.9007	.9533	.9373
3.0	.200	.5773	.4753	.6927	.1753	.6553	.6627	.5900
5.0	.200	.3047	.2087	.4753	.1300	.5213	.4280	.3280
1.0	.500	1.0000	1.0000	1.0000	.9980	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	.9907	1.0000	1.0000	1.0000
3.0	.500	.9967	.9947	.9993	.8460	.9967	.9967	.9980
5.0	.500	.8800	.7907	.9447	.6653	.9627	.9153	.8840

TABLE B-2b. Powers of trend detection for normal errors with fifteen years of data and with a seasonal pattern of variances (high, low, high, low)

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0540	.0547	.0587	.0473	.0547	.0547	.0547
1.5	.000	.0533	.0507	.0627	.0413	.0420	.0540	.0540
3.0	.000	.0533	.0547	.0627	.0407	.0453	.0547	.0527
5.0	.000	.0527	.0493	.0500	.0433	.0480	.0500	.0480
1.0	.002	.0533	.0547	.0680	.0473	.0560	.0600	.0587
1.5	.002	.0640	.0647	.0720	.0487	.0567	.0607	.0607
3.0	.002	.0467	.0487	.0527	.0493	.0460	.0507	.0487
5.0	.002	.0420	.0433	.0553	.0453	.0447	.0480	.0467
1.0	.005	.0853	.0840	.0827	.0700	.0740	.0813	.0820
1.5	.005	.0687	.0680	.0827	.0653	.0693	.0813	.0813
3.0	.005	.0533	.0520	.0667	.0553	.0600	.0613	.0573
5.0	.005	.0567	.0553	.0667	.0687	.0673	.0620	.0640
1.0	.020	.7300	.7280	.7307	.6213	.6693	.7233	.7200
1.5	.020	.5300	.5193	.5527	.4660	.5020	.5360	.5347
3.0	.020	.2107	.1940	.3053	.3080	.3493	.2840	.2700
5.0	.020	.1180	.1080	.2120	.2680	.2920	.1953	.1900
1.0	.050	1.0000	1.0000	1.0000	.9987	1.0000	1.0000	1.0000
1.5	.050	.9993	.9993	.9987	.9953	.9987	.9987	.9987
3.0	.050	.8433	.8353	.9413	.9487	.9720	.9280	.9347
5.0	.050	.4607	.4360	.7647	.9067	.9260	.7427	.7453
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-2c. Powers of trend detection for normal errors with twenty-five years of data and with a seasonal pattern of variances {high, low, high, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for coy.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0513	.0513	.0573	.0513	.0520	.0493	.0520
1.5	.000	.0573	.0573	.0607	.0493	.0507	.0553	.0547
3.0	.000	.0440	.0453	.0447	.0340	.0327	.0440	.0453
5.0	.000	.0473	.0473	.0453	.0433	.0453	.0447	.0460
1.0	.002	.0887	.0860	.0933	.0787	.0873	.0913	.0893
1.5	.002	.0700	.0693	.0680	.0667	.0713	.0673	.0693
3.0	.002	.0700	.0693	.0713	.0633	.0673	.0693	.0693
5.0	.002	.0547	.0553	.0700	.0593	.0627	.0633	.0640
1.0	.005	.2940	.2947	.2993	.2513	.2693	.2860	.2867
1.5	.005	.1960	.1960	.2000	.1820	.1967	.1993	.1993
3.0	.005	.0967	.0947	.1333	.1373	.1507	.1307	.1267
5.0	.005	.0667	.0653	.1013	.1427	.1367	.1013	.0987
1.0	.020	1.0000	1.0000	1.0000	.9993	1.0000	1.0000	1.0000
1.5	.020	.9940	.9940	.9940	.9920	.9940	.9933	.9933
3.0	.020	.7340	.7287	.8667	.9313	.9427	.8613	.8627
5.0	.020	.3580	.3447	.6480	.8607	.8780	.6280	.6273
1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.050	.9833	.9813	1.0000	1.0000	1.0000	.9993	1.0000
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-3a. Powers of trend detection for lognormal errors with five years of data and with a seasonal pattern of variances {low, high, low, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0380	.0327	.0467	.0053	.0373	.0480	.0367
1.5	.000	.0467	.0427	.0607	.0073	.0380	.0627	.0527
3.0	.000	.0327	.0333	.0473	.0060	.0320	.0513	.0473
5.0	.000	.0347	.0440	.0460	.0047	.0373	.0487	.0487
1.0	.002	.0467	.0387	.0527	.0073	.0320	.0473	.0433
1.5	.002	.0453	.0400	.0573	.0087	.0427	.0547	.0420
3.0	.002	.0413	.0407	.0600	.0113	.0440	.0593	.0467
5.0	.002	.0373	.0480	.0567	.0107	.0353	.0480	.0447
1.0	.005	.0507	.0387	.0687	.0093	.0493	.0707	.0607
1.5	.005	.0380	.0340	.0560	.0100	.0427	.0640	.0513
3.0	.005	.0360	.0380	.0540	.0093	.0420	.0607	.0513
5.0	.005	.0347	.0480	.0573	.0127	.0400	.0627	.0553
1.0	.020	.1033	.0787	.1547	.0247	.1467	.1833	.1573
1.5	.020	.0860	.0747	.1440	.0260	.1307	.1547	.1393
3.0	.020	.0680	.0580	.1273	.0233	.1240	.1487	.1193
5.0	.020	.0493	.0500	.1140	.0213	.1060	.1200	.1060
1.0	.050	.3953	.3273	.5473	.1347	.5487	.5973	.5507
1.5	.050	.3367	.2593	.4907	.1400	.5000	.5773	.5300
3.0	.050	.2453	.1820	.3933	.1140	.4220	.4327	.3653
5.0	.050	.1413	.1113	.3307	.0847	.3833	.3513	.2793
1.0	.200	.9693	.9420	.9953	.9227	.9987	.9967	.9953
1.5	.200	.9427	.9060	.9880	.8840	.9947	.9947	.9947
3.0	.200	.8480	.7700	.9707	.8207	.9847	.9820	.9753
5.0	.200	.7127	.5920	.9427	.7647	.9773	.9313	.8860
1.0	.500	.9993	.9980	1.0000	.9993	1.0000	1.0000	1.0000
1.5	.500	.9987	.9920	1.0000	.9987	1.0000	1.0000	1.0000
3.0	.500	.9900	.9740	1.0000	.9940	1.0000	1.0000	1.0000
5.0	.500	.9513	.9093	1.0000	.9887	1.0000	1.0000	1.0000

TABLE B-3b. Powers of trend detection for lognormal errors with fifteen years of data and with a seasonal pattern of variances {low, high, low, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0507	.0500	.0467	.0460	.0487	.0500	.0487
1.5	.000	.0480	.0460	.0573	.0433	.0500	.0487	.0500
3.0	.000	.0473	.0440	.0513	.0487	.0547	.0553	.0533
5.0	.000	.0320	.0320	.0367	.0413	.0427	.0433	.0460
1.0	.002	.0580	.0580	.0913	.0840	.1040	.0940	.0940
1.5	.002	.0580	.0540	.0800	.0847	.0960	.0993	.0967
3.0	.002	.0453	.0467	.0660	.0707	.0833	.0827	.0813
5.0	.002	.0360	.0380	.0600	.0700	.0760	.0740	.0687
1.0	.005	.1180	.1120	.2773	.3020	.3520	.3240	.3220
1.5	.005	.1173	.1113	.2580	.2873	.3073	.3027	.3027
3.0	.005	.0760	.0727	.1673	.2180	.2447	.2160	.2153
5.0	.005	.0733	.0700	.1660	.2060	.2393	.1993	.1927
1.0	.020	.7813	.7700	.9900	.9920	.9960	.9907	.9900
1.5	.020	.7333	.7200	.9847	.9880	.9927	.9920	.9913
3.0	.020	.4927	.4660	.9147	.9707	.9807	.9440	.9493
5.0	.020	.3093	.2847	.8620	.9613	.9733	.8713	.8793
1.0	.050	.9927	.9920	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	.9873	.9853	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	.9400	.9320	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.050	.8007	.7800	1.0000	1.0000	1.0000	.9987	1.0000
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	.9993	.9993	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	.9980	.9973	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-3c. Powers of trend detection for lognormal errors with twenty-five years of data and with a seasonal pattern of variances {low, high, low, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0460	.0433	.0513	.0480	.0560	.0487	.0473
1.5	.000	.0393	.0360	.0460	.0493	.0507	.0513	.0520
3.0	.000	.0493	.0507	.0513	.0527	.0587	.0553	.0527
5.0	.000	.0460	.0433	.0447	.0467	.0493	.0460	.0467
1.0	.002	.0973	.0940	.2433	.2813	.3020	.2693	.2653
1.5	.002	.0840	.0820	.1813	.2333	.2487	.2347	.2347
3.0	.002	.0593	.0613	.1413	.2133	.2320	.1847	.1813
5.0	.002	.0513	.0513	.1193	.1967	.2080	.1547	.1527
1.0	.005	.3887	.3793	.8560	.8947	.9260	.8693	.8687
1.5	.005	.3193	.3147	.7620	.8493	.8680	.8400	.8393
3.0	.005	.1733	.1620	.5973	.7653	.7933	.6760	.6767
5.0	.005	.1280	.1277	.5113	.7300	.7653	.5640	.5660
1.0	.020	.9893	.9893	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.020	.9887	.9873	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.020	.8987	.8927	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.020	.7220	.7047	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	.9973	.9973	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.050	.9833	.9820	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-4a. Powers of trend detection for lognormal errors with five years of data and with a seasonal pattern of variances {high, low, high, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0380	.0327	.0467	.0053	.0373	.0460	.0360
1.5	.000	.0473	.0393	.0533	.0073	.0380	.0567	.0427
3.0	.000	.0393	.0360	.0527	.0060	.0320	.0493	.0467
5.0	.000	.0340	.0347	.0500	.0047	.0373	.0447	.0400
1.0	.002	.0467	.0387	.0527	.0073	.0320	.0487	.0453
1.5	.002	.0433	.0353	.0560	.0107	.0407	.0600	.0507
3.0	.002	.0480	.0413	.0627	.0113	.0413	.0620	.0520
5.0	.002	.0320	.0353	.0507	.0093	.0380	.0520	.0500
1.0	.005	.0507	.0387	.0687	.0093	.0493	.0660	.0553
1.5	.005	.0440	.0373	.0567	.0093	.0400	.0580	.0480
3.0	.005	.0307	.0327	.0480	.0087	.0347	.0580	.0513
5.0	.005	.0393	.0387	.0553	.0140	.0420	.0520	.0533
1.0	.020	.1033	.0787	.1547	.0247	.1467	.1800	.1493
1.5	.020	.0813	.0673	.1240	.0200	.1093	.1460	.1267
3.0	.020	.0587	.0487	.0987	.0120	.0807	.0980	.0827
5.0	.020	.0400	.0367	.0807	.0193	.0740	.0753	.0587
1.0	.050	.3953	.3273	.5473	.1347	.5487	.6180	.5627
1.5	.050	.2720	.2173	.4220	.1073	.4473	.5147	.4753
3.0	.050	.1380	.1000	.2707	.0647	.2967	.2653	.2067
5.0	.050	.0940	.0787	.1860	.0467	.2407	.1653	.1327
1.0	.200	.9693	.9420	.9953	.9227	.9987	.9967	.9947
1.5	.200	.9920	.8860	.9847	.8500	.9920	.9947	.9927
3.0	.200	.7433	.6507	.9040	.6413	.9413	.9367	.9160
5.0	.200	.5147	.4020	.7713	.5153	.8633	.7467	.6613
1.0	.500	.9993	.9980	1.0000	.9993	1.0000	1.0000	1.0000
1.5	.500	.9960	.9893	1.0000	.9980	1.0000	1.0000	1.0000
3.0	.500	.9733	.9507	.9967	.9793	.9993	.9993	.9987
5.0	.500	.9033	.8367	.9820	.9087	.9953	.9913	.9887

TABLE B-4b. Powers of trend detection for lognormal errors with fifteen years of data and with a seasonal pattern of variances {high, low, high, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0507	.0500	.0467	.0460	.0487	.0507	.0507
1.5	.000	.0460	.0487	.0460	.0433	.0500	.0500	.0507
3.0	.000	.0453	.0440	.0507	.0487	.0547	.0580	.0553
5.0	.000	.0387	.0387	.0427	.0413	.0427	.0453	.0447
1.0	.002	.0580	.0580	.0913	.0840	.1040	.0987	.0947
1.5	.002	.0620	.0587	.0773	.0793	.0887	.0940	.0933
3.0	.002	.0427	.0453	.0480	.0580	.0627	.0613	.0613
5.0	.002	.0460	.0507	.0540	.0600	.0587	.0593	.0600
1.0	.005	.1180	.1120	.2773	.3020	.3520	.3233	.3200
1.5	.005	.1000	.0987	.2193	.2467	.2600	.2627	.2633
3.0	.005	.0687	.0613	.1187	.1520	.1720	.1313	.1273
5.0	.005	.0440	.0427	.0847	.1353	.1453	.0913	.0920
1.0	.020	.7813	.7700	.9900	.9920	.9960	.9887	.9887
1.5	.020	.6720	.6600	.9653	.9747	.9860	.9793	.9787
3.0	.020	.3553	.3413	.7407	.8987	.9187	.7867	.7867
5.0	.020	.1693	.1573	.5193	.8207	.8487	.5207	.5107
1.0	.050	.9927	.9920	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	.9753	.9740	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	.8647	.8487	.9993	1.0000	1.0000	1.0000	1.0000
5.0	.050	.6120	.5993	.9780	1.0000	1.0000	.9813	.9867
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	.9980	.9980	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	.9953	.9947	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	.9993	.9993	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-4c. Powers of trend detection for lognormal errors with twenty-five years of data and with a seasonal pattern of variances {high, low, high, low}

Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
1.0	.000	.0460	.0433	.0513	.0480	.0560	.0547	.0527
1.5	.000	.0460	.0433	.0447	.0493	.0507	.0513	.0527
3.0	.000	.0427	.0447	.0447	.0527	.0587	.0573	.0580
5.0	.000	.0527	.0513	.0427	.0467	.0493	.0493	.0507
1.0	.002	.0973	.0940	.2433	.2813	.3020	.2607	.2593
1.5	.002	.0760	.0747	.1613	.1940	.2020	.1867	.1880
3.0	.002	.0587	.0547	.1027	.1533	.1620	.1167	.1153
5.0	.002	.0553	.0573	.0727	.1187	.1180	.0887	.0847
1.0	.005	.3887	.3793	.8560	.8947	.9260	.8487	.8507
1.5	.005	.2733	.2693	.6847	.7820	.8093	.7653	.7647
3.0	.005	.1247	.1227	.3533	.6007	.6207	.4167	.4200
5.0	.005	.0687	.0700	.2367	.4873	.5087	.2527	.2433
1.0	.020	.9893	.9893	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.020	.9740	.9727	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.020	.7873	.7767	.9960	1.0000	1.0000	.9993	.9993
5.0	.020	.4753	.4547	.9720	1.0000	1.0000	.9753	.9787
1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.050	.9987	.9987	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.050	.9920	.9920	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.050	.9953	.9493	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1.5	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
3.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-5a. Powers of trend detection for correlated normal errors with five years of data and with a seasonal pattern of variances {low, high, low, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.0927	.0713	.1040	.0053	.0607	.0867	.0733
.2	5.0	.000	.0573	.0760	.1080	.0113	.0693	.0893	.0753
.2	1.0	.002	.0887	.0687	.1033	.0113	.0633	.0907	.0680
.2	5.0	.002	.0627	.0880	.1007	.0080	.0640	.0913	.0867
.2	1.0	.005	.0973	.0800	.1120	.0060	.0707	.1033	.0793
.2	5.0	.005	.0660	.0767	.1093	.0053	.0647	.0933	.0887
.2	1.0	.020	.1267	.1000	.1367	.0113	.0867	.1220	.1013
.2	5.0	.020	.0653	.0840	.1100	.0087	.0847	.0993	.0833
.2	1.0	.050	.2693	.2367	.2847	.0240	.1733	.2593	.2280
.2	5.0	.050	.0960	.0920	.1727	.0147	.1380	.1607	.1333
.2	1.0	.200	.9927	.9873	.9907	.4480	.9600	.9907	.9840
.2	5.0	.200	.5447	.3640	.7793	.2867	.7913	.7500	.6453
.2	1.0	.500	1.0000	1.0000	1.0000	.9980	1.0000	1.0000	1.0000
.2	5.0	.500	.9807	.9060	.9987	.9387	.9993	.9940	.9893
.4	1.0	.000	.1740	.1427	.1813	.0140	.1153	.1727	.1440
.4	5.0	.000	.0993	.0927	.1727	.0107	.1173	.1540	.1247
.4	1.0	.002	.1660	.1313	.1693	.0080	.1213	.1520	.1307
.4	5.0	.002	.1100	.1053	.1673	.0113	.1227	.1613	.1467
.4	1.0	.005	.1767	.1493	.1807	.0107	.1160	.1700	.1453
.4	5.0	.005	.0987	.0980	.1700	.0067	.1273	.1520	.1273
.4	1.0	.020	.1907	.1593	.2053	.0140	.1387	.1807	.1493
.4	5.0	.020	.1033	.0987	.1813	.0100	.1353	.1600	.1393
.4	1.0	.050	.3280	.2793	.3300	.0307	.2427	.3220	.2787
.4	5.0	.050	.1347	.1027	.2320	.0233	.1827	.2227	.1773
.4	1.0	.200	.9847	.9753	.9747	.4240	.9447	.9793	.9640
.4	5.0	.200	.5227	.3547	.7640	.2527	.7867	.7193	.6173
.4	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.500	.9673	.8880	.9967	.9180	.9967	.9887	.9767

TABLE B-5b. Powers of trend detection for correlated normal errors with fifteen years of data and with a seasonal pattern of variances {low, high, low, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.0853	.0813	.0887	.0407	.0767	.0867	.0873
.2	5.0	.000	.0733	.0727	.0967	.0520	.0940	.0967	.0940
.2	1.0	.002	.1067	.1080	.1187	.0527	.0960	.1053	.1047
.2	5.0	.002	.0773	.0753	.1013	.0513	.0933	.1020	.0980
.2	1.0	.005	.1473	.1487	.1520	.0873	.1360	.1493	.1480
.2	5.0	.005	.0927	.0873	.1227	.0720	.1113	.1193	.1193
.2	1.0	.020	.7320	.7267	.7253	.5120	.6553	.7060	.7000
.2	5.0	.020	.1947	.1653	.4100	.3367	.4647	.3993	.3927
.2	1.0	.050	1.0000	1.0000	1.0000	.9967	1.0000	1.0000	1.0000
.2	5.0	.050	.6967	.6580	.9740	.9747	.9887	.9693	.9753
.2	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.000	.1920	.1827	.1967	.0667	.1707	.1827	.1807
.4	5.0	.000	.1293	.1167	.1853	.0893	.1753	.1787	.1767
.4	1.0	.002	.2067	.2027	.2080	.0847	.1760	.1973	.1947
.4	5.0	.002	.1220	.1087	.1847	.0687	.1780	.1760	.1707
.4	1.0	.005	.2313	.2227	.2307	.0833	.2000	.2253	.2207
.4	5.0	.005	.1233	.1120	.1807	.0773	.1807	.1793	.1740
.4	1.0	.020	.6787	.6767	.6713	.4407	.6313	.6693	.6633
.4	5.0	.020	.2427	.2207	.4633	.3033	.5107	.4567	.4500
.4	1.0	.050	.9993	.9993	.9993	.9933	.9980	.9993	.9993
.4	5.0	.050	.6700	.6260	.9413	.9113	.9707	.9320	.9373
.4	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-5c. Powers of trend detection for correlated normal errors with twenty-five years of data and with a seasonal pattern of variances {low, high, low, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.0973	.0967	.1060	.0500	.0927	.0980	.0973
.2	5.0	.000	.0707	.0687	.1047	.0613	.1000	.1020	.1007
.2	1.0	.002	.1293	.1253	.1260	.0680	.1220	.1227	.1200
.2	5.0	.002	.0793	.0773	.0973	.0687	.1153	.0953	.0947
.2	1.0	.005	.3300	.3293	.3420	.2227	.3060	.3180	.3173
.2	5.0	.005	.1073	.0980	.1913	.1380	.2273	.1820	.1800
.2	1.0	.020	.9987	.9987	.9987	.9947	.9993	.9987	.9987
.2	5.0	.020	.5707	.5440	.9313	.9433	.9733	.9287	.9327
.2	1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.050	.9987	.9993	1.0000	1.0000	1.0000	1.0000	1.0000
.2	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.000	.1907	.1880	.1893	.0720	.1760	.1813	.1800
.4	5.0	.000	.1133	.1087	.1687	.0733	.1853	.1693	.1647
.4	1.0	.002	.2233	.2213	.2207	.0940	.2120	.2187	.2160
.4	5.0	.002	.1180	.1140	.1887	.0860	.1913	.1833	.1773
.4	1.0	.005	.3833	.3807	.3840	.2120	.3667	.3760	.3747
.4	5.0	.005	.1733	.1627	.2760	.1547	.2893	.2727	.2647
.4	1.0	.020	.9933	.9933	.9940	.9673	.9927	.9940	.9933
.4	5.0	.020	.5867	.5620	.9047	.8780	.9540	.9053	.9060
.4	1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.050	.9947	.9947	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-6a. Powers of trend detection for correlated normal errors with five years of data and with a seasonal pattern of variances {high, low, high, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.1007	.0860	.1167	.0160	.0647	.0980	.0773
.2	5.0	.000	.0760	.0627	.1000	.0093	.0613	.0973	.0733
.2	1.0	.002	.1020	.0873	.1267	.0087	.0787	.1053	.0867
.2	5.0	.002	.0727	.0573	.0993	.0067	.0647	.0947	.0807
.2	1.0	.005	.0960	.0793	.1107	.0093	.0640	.0907	.0753
.2	5.0	.005	.0727	.0567	.0993	.0107	.0627	.0873	.0680
.2	1.0	.020	.1220	.1033	.1353	.0120	.0847	.1267	.1040
.2	5.0	.020	.0687	.0527	.1093	.0067	.0800	.0987	.0767
.2	1.0	.050	.2700	.2320	.2807	.0233	.1987	.2613	.2300
.2	5.0	.050	.0807	.0660	.1140	.0153	.1067	.1080	.0840
.2	1.0	.200	.9887	.9793	.9840	.4293	.9567	.9840	.9800
.2	5.0	.200	.3180	.2093	.4773	.1480	.5267	.4373	.3460
.2	1.0	.500	1.0000	1.0000	1.0000	.9960	1.0000	1.0000	1.0000
.2	5.0	.500	.8847	.7880	.9440	.6373	.9600	.9160	.8747
.4	1.0	.000	.1673	.1407	.1753	.0127	.1387	.1633	.1360
.4	5.0	.000	.1167	.0860	.1593	.0147	.1207	.1567	.1160
.4	1.0	.002	.1840	.1440	.1927	.0140	.1333	.1733	.1440
.4	5.0	.002	.1007	.0753	.1507	.0093	.1073	.1480	.1220
.4	1.0	.005	.1653	.1340	.1793	.0153	.1173	.1653	.1327
.4	5.0	.005	.1093	.0893	.1633	.0107	.1200	.1453	.1180
.4	1.0	.020	.1967	.1587	.2053	.0140	.1307	.1840	.1520
.4	5.0	.020	.1120	.0793	.1587	.0133	.1220	.1400	.1133
.4	1.0	.050	.3360	.2880	.3467	.0293	.2507	.3113	.2807
.4	5.0	.050	.1280	.0960	.1853	.0160	.1533	.1680	.1380
.4	1.0	.200	.9820	.9747	.9773	.4420	.9467	.9760	.9680
.4	5.0	.200	.3607	.2560	.4873	.1527	.5313	.4687	.3807
.4	1.0	.500	1.0000	1.0000	1.0000	.9960	1.0000	1.0000	1.0000
.4	5.0	.500	.8720	.7820	.9380	.6187	.9560	.9140	.8647

TABLE B-6b. Powers of trend detection for correlated normal errors with fifteen years of data and with a seasonal pattern of variances {high, low, high, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.1140	.1140	.1187	.0540	.0907	.1100	.1067
.2	5.0	.000	.0840	.0800	.1120	.0580	.1027	.1040	.1000
.2	1.0	.002	.1200	.1173	.1267	.0553	.0973	.1193	.1167
.2	5.0	.002	.0780	.0780	.0993	.0513	.0893	.0960	.0933
.2	1.0	.005	.1587	.1533	.1627	.0753	.1313	.1540	.1507
.2	5.0	.005	.0727	.0687	.1093	.0567	.1013	.0993	.0973
.2	1.0	.020	.7213	.7160	.7167	.5267	.6747	.7100	.7053
.2	5.0	.020	.1393	.1267	.2293	.2107	.2927	.2233	.2180
.2	1.0	.050	1.0000	1.0000	1.0000	.9980	1.0000	1.0000	1.0000
.2	5.0	.050	.4707	.4480	.7293	.8227	.9013	.7087	.7067
.2	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.000	.1833	.1753	.1800	.0633	.1500	.1787	.1773
.4	5.0	.000	.1313	.1287	.1633	.0780	.1667	.1527	.1493
.4	1.0	.002	.2047	.1987	.2047	.0787	.1740	.1993	.1980
.4	5.0	.002	.1320	.1267	.1713	.0847	.1740	.1640	.1600
.4	1.0	.005	.2373	.2353	.2360	.0980	.2000	.2207	.2180
.4	5.0	.005	.1333	.1240	.1687	.0773	.1793	.1660	.1553
.4	1.0	.020	.6793	.6740	.6833	.4453	.6447	.6740	.6673
.4	5.0	.020	.1907	.1820	.2973	.2027	.3673	.2860	.2767
.4	1.0	.050	1.0000	1.0000	1.0000	.9900	.9993	1.0000	1.0000
.4	5.0	.050	.4707	.4473	.7067	.7227	.8533	.6887	.6840
.4	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

TABLE B-6c. Powers of trend detection for correlated normal errors with twenty-five years of data and with a seasonal pattern of variances {high, low, high, low}

p	Ratio of std. dev	Slope	Anal. of covar.	Modified t	Mann-Ken. on deseas. data	Seas. Ken. w/correc. for cov.	Seas. Ken. w/o correc. for cov.	Anal. of cov. on ranks	Modified t on ranks
.2	1.0	.000	.1027	.0993	.1067	.0500	.0920	.1040	.1013
.2	5.0	.000	.0733	.0707	.0947	.0613	.1013	.0947	.0873
.2	1.0	.002	.1380	.1367	.1353	.0753	.1233	.1293	.1287
.2	5.0	.002	.0860	.0820	.1127	.0720	.1233	.1133	.1127
.2	1.0	.005	.3347	.3333	.3280	.2100	.3027	.3207	.3220
.2	5.0	.005	.0880	.0847	.1307	.0953	.1653	.1200	.1167
.2	1.0	.020	.9993	.9993	1.0000	.9927	1.0000	.9993	.9993
.2	5.0	.020	.3440	.3360	.6060	.7333	.8293	.5960	.5940
.2	1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.050	.9693	.9693	.9987	1.0000	1.0000	.9980	.9980
.2	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.2	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.000	.1927	.1880	.1900	.0793	.1727	.1887	.1860
.4	5.0	.000	.1187	.1133	.1580	.0673	.1700	.1533	.1460
.4	1.0	.002	.2233	.2187	.2220	.0947	.2087	.2113	.2087
.4	5.0	.002	.1393	.1400	.1767	.0867	.1980	.1753	.1707
.4	1.0	.005	.3560	.3487	.3480	.1907	.3267	.3413	.3360
.4	5.0	.005	.1480	.1467	.2113	.1160	.2447	.2080	.2067
.4	1.0	.020	.9973	.9973	.9980	.9747	.9960	.9973	.9973
.4	5.0	.020	.3873	.3720	.6147	.6320	.7980	.6100	.6033
.4	1.0	.050	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.050	.9387	.9367	.9947	1.0000	1.0000	.9927	.9953
.4	1.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.200	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	1.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
.4	5.0	.500	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

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